Design and evaluation of a cognitive approach for disseminating semantic knowledge and content in opportunistic networks

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ABSTRACT

In cyber-physical convergence scenarios information flows seamlessly between the physical and the cyber worlds. Here, users’ mobile devices represent a natural bridge through which users process acquired information and perform actions. The sheer amount of data available in this context calls for novel, autonomous and lightweight data-filtering solutions, where only relevant information is finally presented to users. Moreover, in many real-world scenarios data is not categorised in predefined topics, but it is generally accompanied by semantic descriptions possibly describing users’ interests. In these complex conditions, user devices should autonomously become aware not only of the existence of data in the network, but also of their semantic descriptions and correlations between them. To tackle these issues, we present a set of algorithms for knowledge and data dissemination in opportunistic networks, based on simple and very effective models (called cognitive heuristics) coming from cognitive sciences. We show how to exploit them to disseminate both semantic data and the corresponding data items. We provide a thorough performance analysis, under various different conditions comparing our results against non-cognitive solutions. Simulation results demonstrate the superior performance of our solution towards a more effective semantic knowledge acquisition and representation, and a more tailored content acquisition.

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1. Introduction

The physical world is becoming more and more saturated by the presence of a vast number of mobile devices. These devices are able to sense data from the physical environment and autonomously elaborate and exchange information among themselves. This behaviour is leading to a constant and increasing flow of information from the physical world to the cyber one and vice versa. In this context, data coming from the physical world impacts on the decisions taken by devices acting in the cyber world, whereas the information spread in the cyber world can, in turn, influence the actions taken in the physical world. This complex information scenario is known as the Cyber–Physical World (CPW) convergence scenario [1–6].

The users’ devices acting in this scenario play a key role, since they represent the “door” to the cyber world through which their human owners can access the massive amount of information available in the cyber world. Indeed, in the CPW convergence scenario users’ personal devices can be regarded as the proxies of their users in the cyber world. They are most of the time together with their users in the physical world, and can thus, for example, gather context information about their behaviour and the physical places they visit. On the other hand, they are probably the most typical way through which users access information in the cyber world. Therefore, they can be usefully instructed to autonomously act in the cyber world (e.g., by proactively filtering or fetching information) on behalf of their users, by exploiting context information about their behaviour in the physical world. To this end, because the cyber world is typically full of data of all kinds that could possibly be accessed, users’ devices should automatically understand which data is important for their users at a given point in time, avoiding to overflow them with useless information.

In this context, the opportunistic networking paradigm plays a relevant role by supporting direct communication between mobile devices. In an opportunistic network, direct, physical contacts between nodes are opportunistically exploited to recognise and disseminate relevant information toward potentially interested nodes, without the need of centralised infrastructures or precomputed paths from source to destination [7–10]. Beyond the problem of data dissemination, it is worth to mention that the other main research issues in opportunistic networks focus on the development
of analytical models of data delivery performance [11–13], routing approaches that consider nodes’ aggregation and privacy [14,15], forwarding schemes for hybrid networks (opportunistic networks combined with the infrastructure [16]), real world implementations [17], applications to Vehicular Networks [18,19]. Recently, opportunistic networks have been proposed as one of the possible key components of future mobile networks (e.g., in the 5G domain), as they are able to complement wireless infrastructures such as cellular and WiFi networks, by enabling direct dissemination of data among users nearby, thus contributing to offload data from the cellular network [20,21].

Generally, in analysing data dissemination in opportunistic networks it is assumed that the users’ interest is rather static and quite simple to describe [22]. In typical data dissemination approaches, users are supposed to be interested in predefined content categories (e.g., sports, movies, etc.) and therefore their devices collect all the contents related to those categories. An aspect that has not been often taken into consideration in the literature on opportunistic networks is that contents are also equipped with rich semantic descriptions (i.e., associated concepts and/or tags). This could be the case, for instance, of tagged photos on Flickr and Instagram, or messages annotated with “hashtags” in Twitter and Facebook. Often, users’ interests toward contents are driven by the content descriptions, which triggers interest in contents themselves: data items are accessed by users because their semantic description contains information that is relevant to the user at that moment. Therefore, our key idea in this paper is to optimise in an intertwined way the dissemination of both semantic data associated to contents, and of contents themselves. Specifically, in the proposed approach semantic data is disseminated among users’ devices, based on the current interests of the users. By receiving semantic data, users’ devices also know what contents (associated to that semantic data) are available in the network, and fetch them, if appropriate. Therefore, in our approach users’ (dynamic) interests drive the dissemination of semantic data, which drives the dissemination of content. As we explain in Section 3, this mechanism is quite similar to the way users access information in the physical world.

Specifically, in this paper we apply concepts coming from the cognitive science field, and design a system whereby users’ devices autonomously become aware of the structure of the semantic information describing the available content in the environment, and disseminate contents based on this knowledge. In particular, we show how devices can exchange information in a way that resembles how conversations between humans enable spreading of ideas (i.e. semantic information), which generates interests for specific types of content, and ultimately determine content that people access. To this end, we consider that, acting on behalf of their users inside the cyber world, mobile devices are exposed to problems similar to the ones faced by the human brain when dealing with the information and content selection tasks. Cognitive scientists produced, during years, many functional models and descriptions of these mental schemes. These functional models, called cognitive heuristics, differently from other biological models as artificial neural networks, do not aim at reproducing the physiology of the brain’s processes, but model their functionality. By taking advantage of these descriptions, previous works [23–25] have shown how rules and procedures used by the human brain, when assessing the relevance of information (in face of time and resource restrictions), can be exploited to design adaptive, low resource-demanding, yet very effective, algorithms for data dissemination in opportunistic networks but none – to the best of our knowledge – has explored how to apply these models to optimise the joint dissemination of semantic information and associated contents.

In order to take advantage of these models, we have to face the problem of how to represent semantic information in devices’ memory, how semantic information is retrieved and exchanged upon contacts between nodes in physical proximity, and how content is finally selected for dissemination, based on the semantic data exchange that has been carried on. For each node, the internal memory representation of semantic concepts is inspired by the associative network models (AN) [26,27] of human memory coming from the cognitive psychology field. In AN models, semantic concepts are represented by nodes that are interconnected by paths that vary in strength, reflecting the degree of association between each pair of concepts. In our proposal, each mobile node builds a local semantic representation of its own contents through a semantic directed weighted graph, where vertices represent the semantic concepts associated to data items, and the edges represent the semantic relationships between concepts, both learnt from the environment and derived from the node’s own contents. Moreover, since memory is a limited resource at each node, cognitive models of how the least relevant information can be dropped from memory [28,29] are exploited. When nodes come in physical proximity (are in contact), exchange of semantic information happens as follows. Communication takes place only between nodes having some common interest, i.e. only if there is an initial set of semantic concepts shared by both nodes. Concepts to be exchanged are selected by navigating each semantic network, according to an edge ranking algorithm derived from the fluency cognitive heuristic [FH] [30,31]. Finally, we show how mobile nodes, after having enriched their semantic graphs with new concepts taken from other encountered nodes, select which contents, locally available at one of the nodes, to exchange between them, giving precedence to contents whose semantic information maximally overlaps with semantic concepts just exchanged between nodes. In cognitive terms this refers to the tallying heuristic (TH) [32], another cognitive decision strategy used by human brain. All these cognitive processes are described in more details in Section 3.

The rest of the paper is organised as follows. In Section 2 we present state-of-the-art data dissemination approaches for opportunistic networks. In Section 3 we show at a high level how each cognitive model relates to our solution. In Section 4 we present the entire approach in full detail. In Section 5 a thorough performance analysis of our cognitive based system is provided and, finally, Section 6 concludes the paper.

2. Related data dissemination approaches

The problem of data dissemination in opportunistic networks have been addressed by many works during years. The first attempt was in the context of the PodNet Project [33]. The authors proposed a solution where nodes cooperatively exchange data items in order to retrieve all those contents they are interested in. Precisely, contents are organised in predetermined channels of interest to which nodes are subscribed. In order to favour the data dissemination, upon encounter, nodes load in a public cache items they are not directly interested in. Items to be maintained in the public cache are chosen depending on different history-based strategies that consider the past received requests, interpreted by nodes as a popularity index of the channel of interest. These strategies could be effective when users mobility is homogeneous and contents can easily traverse the network. However, this approach suffers in scenarios where nodes tend to group in communities and their movements are heterogeneous.

Advances in data dissemination solutions leave the content-centric approach adopted in PodNet in favour of more user-centric solutions. Precisely, these solutions define more elaborate

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1 In the paper we use the terms content and data item interchangeably.
heuristics that exploit social information about users – e.g. users’ interests and social relationships – in order to improve the performance of data dissemination. ContentPlace [34] is a social aware dissemination system that proposes a general framework for designing data dissemination policies. In ContentPlace, during a contact nodes fill their local caches (with contents they either already have or they fetch from the other node) to maximise both the local utility (i.e. satisfy the interests of the local user) and the global utility (i.e. satisfy the interests of other nodes in the local user’s communities). In [35] authors propose a social-aware solution to find the optimal placement of a given piece of content in an opportunistic network. The idea is to iteratively migrate contents to nodes that are increasingly “central” to the overall network, i.e. nodes such that the average cost of accessing the content from any other interested node is increasingly lower. Social-aware data dissemination generally results in a quicker and more fair content dissemination with respect to social-oblivious policies. The overhead introduced for collecting and managing the information needed by these algorithms (e.g., contact patterns, social structures, etc.) typically pays off as content can be replicated less aggressively (and more precisely), and the total network traffic typically turns out to be lower than in social-oblivious schemes.

Other works apply the publish/subscribe framework – a content-centric overlay initially conceived to run on top of static networks [36] – to opportunistic networks, by adapting the conventional definitions of publisher, subscriber and broker. Accordingly, in [37] the authors presented a pub/sub social-based and topic-based data dissemination solution. Brokers are the most central (i.e. popular) nodes in the community and communities are identified through an on-line community detection algorithm. New data items to be diffused are sent to the broker of the community. If some node is subscribed to that topic within the community, the item is broadcast. Moreover, the item is also sent to other brokers if their community members are subscribed to that topic.

Other approaches take in account information about patterns of encounters. In SocialCast [38] nodes disseminate the information about their channels of interest. Every node uses this information combined with its own pattern of encounters to compute a utility value for each channel of interest. This value is then used to decide if the next encountered node would be a good carrier for a given data item. In PrefCast [39] authors assume that the utility of disseminating the same content varies with time. Considering limited contacts durations, nodes compute a forwarding schedule to prioritise dissemination of contents that are predicted to be more requested in the near future.

Other approaches for data dissemination consider solutions based on global utility functions to be solved as a global optimisation problem, where nodes’ individual caches are viewed as a big, cumulative caching space. Reich and Chaintreau [40], for example, focus on the problem of finding a global optimal allocation for a set of content items assuming that users are impatient, i.e., users’ interest for items monotonically decreases with time. Although such global optimisation approach can find the optimal policy and lead to an optimal content allocation, it requires global knowledge of the network and a-priori information on how users behave, that in practice, might be unlikely to be available in an opportunistic scenario.

The use of cognitive heuristics to drive the dissemination process has been first proposed in [23]. The idea is to drive the dissemination process using procedures that mimic, in functional terms, the human decision making process. To this end, two of the several cognitive models present in the psychological literature are considered [41]: the Recognition Heuristic and the Take the Best Heuristic. Precisely, nodes use the Recognition heuristic to become aware of which are the most popular channels of interest in the system and what are the corresponding contents that should be further replicated in order to satisfy all the interested users. This work proves the suitability and effectiveness of these heuristics in problems, like data dissemination in opportunistic networks, where every node has only a partial knowledge about its environment. However, due to the great number of status information the nodes have to maintain, this approach may suffer from scalability problems. In [24] an improved solution addressed those scalability problems. Nodes exploit, beyond cognitive heuristics, (i) a local aggregate measure about items diffusion and (ii) a stochastic mechanism to choose which data items should be replicated. The resulting solution shows to be more efficient and scalable than the previous one and, thanks to the stochastic decision making mechanism, independent of specific scenario configurations.

Another different but connected solution presented in the literature takes into account the semantic side of data shared in an opportunistic network [42]. Precisely, starting from semantic data annotations given by the users, each node builds a semantic network representing that information. Upon contacts, nodes exchange useful information present in their semantic networks which is thus disseminated in the entire network. That work represents the first attempt to exchange semantic information exploiting cognitive mechanisms in opportunistic networks.

In this paper (which extends our previous work [43]) the ideas of [42] are exploited to design a more complete cognitive-based solution for both knowledge (semantic information) and content dissemination. The main extensions with respect to [43] include a more detailed description of all the cognitive models and concepts exploited in this proposal, a more thorough presentation of the algorithms developed from the cognitive science models, and a more extensive set of simulation results. These results analyse the performance of the system from both the semantic knowledge and the content dissemination points of view, using different metrics and under different settings of the main parameters of the system. Moreover, we compared the proposed solution with another algorithm for semantic and content dissemination that is not based on cognitive models. We find that the proposed solution is much more efficient in retrieving and keeping in memory the most relevant semantic information and it acquires the relevant content associated with this information more rapidly than the benchmark solution.

We point out that part of the semantic-driven exchange of information process described in this paper is also used in [44]. Specifically, in [44] cognitive-based methods are used to exchange semantic information, in order to let mobile nodes become aware of the features that describe the physical locations in the environment around them. Semantic data is generated by the physical locations and it is spread by both physical locations and mobile devices. With respect to that work, in this paper we exploit the opportunistic semantic knowledge dissemination mechanism for different purposes and under different conditions. Specifically, in this work we use a semantic exchange of information in a pure opportunistic network, i.e. contacts between mobile devices are the only way to exchange and disseminate information. Content is generated and spread only by the devices. These facts determine a different behaviour of the two systems and require changes between the two solutions, specifically in the definition of the key algorithms of the proposed approach (see Section 4.3). Moreover, in this paper we do not propose a simple semantic data dissemination scheme. Rather, semantic information is used to drive the spreading of the data items from which the semantic descriptions are taken. In order to achieve this goal, other mechanisms are needed in addition to the semantic dissemination scheme. To this end, we propose to exploit another lightweight, context-aware, cognitive-based process for the dissemination of data items, which is driven by the dissemination of the associated semantic data.
3. High-level overview

In this section we provide a high level overview of our approach. Namely we provide a direct mapping between the aspects of memory representation, concept retrieval and content selection, and the cognitive models we exploit to define the building blocks of our approach.

3.1. Memory representation

The first aspect of our solution concerns the representation and organisation of the semantic information about content in nodes’ memory. The organisation of the semantic information is a very common task that the human memory solves very well. Thus, we used one of the memory models present in the cognitive science field. Recently, two categories of models are significantly well established in the literature, namely, the Associative Network Models and the Connectionist Models [26, 27].

In Associative Network Models, concepts are represented by nodes that are interconnected by pathways that vary in strength, reflecting the degree of association between each pair of concepts. Two related concepts are connected by links, whose weight represents the activation level, i.e. how likely it is that one of them is “accessed” after the other has been accessed. The details of how these weights are computed are provided in Section 4.1.

Connectionist Models represent an alternative to Associative Network Models. These models treat the problem of mental representation as weighted combination of fixed set of features [45]. Though the Connectionist models share some terminology and ideas with the Associative Network Models, they follow a very different metaphor. Precisely, they consider the memory as a large network of feature units (nodes) that share activation through weighted connections (pathways). Therefore, in these kind of networks, concepts representation are distributed across the entire network and this generates a process that is very similar to what happens in biological neural networks. Indeed, the activation of units is affected by the weights of the incoming links that can be either positive or negative. Such models are more sophisticated than the associative network models described before, but they are also more complex, i.e. in order to converge to a good representation of concepts they must be trained and the training process is typically very slow.

In our work we use Associative Network Models and precisely Associative Semantic Networks due to their simplicity and usability. In our solution nodes of the ASN represent semantic concepts describing the content in the system. Nodes relations are represented by weighted edges. In Fig. 1 an example of Associative Semantic Network is reported.

3.2. Concept retrieval

The second aspect is about the way the semantic information (knowledge) circulates in the network. Here also, we exploit mechanisms coming from the cognitive science field and resembling the process of information exchange between people during a conversation. We model information exchange when nodes encounter as a conversation between two individuals who meet. We assume that the conversation begins from concepts that people have in common – i.e. concepts present in all participants semantic networks – and that the exchange of semantic concepts consists in the exploration/navigation of the reciprocal semantic networks. There are two principal ways to explore an Associative Semantic Network: sequentially or in parallel, which broadly corresponds to depth-first and breadth-first navigation in standard graph theory, respectively [46]. Parallel processing is particularly appropriate to model the spontaneous activation of knowledge that occurs in absence of a particular goal. Sequential search, instead, well characterises a goal-directed search of memory in pursuit of a specified objective. A sequential search (SS) on AN starts with an activated
concept (key-concept) and proceeds node by node along the path-
way that connects them. When a node has many outgoing paths,
the one with the strongest activation (weight) is selected. If a “dead
end” is reached, the search is re-initiated. Here, we concentrate on
the sequential search model (SS) due to its better pertinence to
our purposes. In fact, in our model each device, starting from a
commonly shared knowledge (the “base of discussion”, in the con-
verson metaphor), uses an information searching mechanism to
retrieve from its memory the most semantically correlated data to
pass to another interacting party. This goal-oriented information
selection process can be better described with the SS model rather
than with a parallel search.

The strongest activation rule is the implementation in this con-
text of the first cognitive heuristic that we use in the paper, i.e. the
Fluency Heuristic (FH). FH is an inference strategy that can be ap-
plied when someone has to choose among two or more alterna-
tives. Among the alternatives that are recognized, the one perceived
as recognized faster is considered to be more important with re-
spect to a selected criterion. Here, being recognized means that a
given information has been found in the environment a sufficient
number of times to let the brain being familiar with it. In the con-
text of the navigation of a semantic network from a given con-
cept, the fluency heuristic dictates that the next concept is the one
linked through the edge with the highest weight, because this is
what allows the brain to retrieve it faster from memory. The details
of how the fluency heuristic is applied to recognise concepts, and
identify those that are exchanged between nodes are presented in
Section 4.3.

3.3. Content selection

The third aspect of our system is the actual data exchange. Here we exploit the mechanism of information exchange during a
conversation. Based on the concepts exchanged during the phase
sketched in Section 3.2, content items are exchanged giving pref-
ERENCE to those that are more “central” with respect to the top-
ics just discussed (i.e. concepts just exchanged). This mechanism
is modelled, in cognitive terms, by the Tallying Heuristic (TH). Pre-
cisely, in order to discriminate among alternatives, TH selects those
alternatives that according to a criterion, have more favourable
cues. In our case, cues are tags associated to data items, and a
tag is favourable if it matches one of the concepts accessed in
their semantic networks by two nodes during an encounter (i.e.,
if the nodes have “spoken” about a concept that matches the tag).
Precisely, for each alternative, TH simply counts the number of
favourable cues without giving any special weight to any of them.
The alternative with the highest number of positive cues is then
selected [32]. Tallying has proved to perform the same or even
better than multiple regression models. As an example, let us con-
sider a conversation between two users, A and B, on how beautiful
mountains are especially during winter. At the end of their conver-
sation, user A remembers that some pictures stored in his smart-
phone are about his last holiday spent on the Alps. Thus, user A
selects those pictures, and shares them with user B. In this ex-
ample, according to the Tallying Heuristic, the pictures are selected
by user A because they are the ones having more favourable cues
with respect to all the other pictures stored in A’s phone.

Details on how this is implemented in our scheme are provided in
Section 4.4

4. Cognitive heuristics for data and content distribution in
opportunistic networks

In this section, we describe in detail how cognitive models
are used to define the building blocks of our data dissemination
system. In Sections 4.1 and 4.2 we describe how semantic infor-
mation (concepts) are stored in memory and dropped. Section 4.3
describes how we use the fluency heuristic to decide which
concepts to exchange between nodes upon encounter. Finally
Section 4.4 describes how we select data items to exchange based
on the tallying heuristic.

4.1. Memory representation of semantic concepts

As anticipated in Section 3.1, one way used by cognitive sci-
entists to describe how humans store their semantic information in
memory is given by the Associative Network models. In these mod-
els, semantic concepts are viewed as nodes and a couple of nodes
is connected whenever the brain is able to establish a relationship
between the involved semantic concepts. These relationships could
have different strengths that vary over time, reflecting the inten-
sity with which the brain perceives those association.

In order to let mobile nodes exploit this cognitive-based mem-
ory organisation, we define each user’s semantic network as a dy-
namic undirected weighted graph $G = (V, E, f(e, t)) : t \in T$, where:

• $t$ is the time at which the graph $G$ is evaluated.
• $V$ is the set of vertices, i.e. the semantic concepts known by
  the node.
• $E$ is the set of edges, i.e. the connections between semantic con-
  cepts the node is able to recall at time $t$.
• $f(e, t)$ is the function that defines the weights of each edge $e \in
  E$ at time $t$.

In a scenario where users actively participate in the creation of
content, we assume that each data item owned by a user is as-
associated to a set of tags – defined by the user herself – that
semantically describe it. This process is similar to what happens in
real social networks like Flickr, Twitter, Instagram, etc. The evolu-
tion of the graph will be clear after explaining the algorithms in
the following sections. For now, it is important to explain how the
graph is initialised at each node at time $t_0$, which is assumed as
the beginning of the evolution of the system\footnote{Without loss of
generality, we assume that all nodes start at time $t_0$. Algorithms
do not change when nodes enter the system at different points in time.}.
For any given user, at time $t_0$, its semantic network defined by $G$ includes all the data
tags associated with the data items locally available at the node,
as its vertices. The set $E$ of the edges of $G$ is created using the fol-
lowing algorithm. Taking one data item at a time, the tags of the
data item are linked together in order to form a completely con-
ected component. After that, the vertices that belong to different
components and have the same label (i.e. they were created from
tags having the same name) are merged together, forming a single
vertex in the final graph $G$. This single vertex inherits all the in-
going and outgoing edges pointing to the original vertices in their
respective connected components.

In order to better clarify this process, Fig. 3 presents an exam-
ple of the mechanism described above. In this example, we assume

![Fig. 3. Creation of a user semantic network at time $t_0$.](image)
that there is a user with two different pictures. Each of the pictures has a set of associated tags. Firstly, two completely connected components are created, one for each of the two pictures. Then, the two components are merged together using the common vertex “lake” as the pivot of this process.

4.2. Memory retention

One of the sources of changes in the nodes’ semantic network, that make it dynamic, is the loss of information, that we model with a forgetting process, as follows. The rationale behind the forgetting process is twofold. On the one hand, it takes into consideration memory limitations at nodes. On the other hand, it mimics the typical behaviour of the human brain, that forgets information that is not accessed for some time. Even disregarding physical memory limitations of devices, such a forgetting process is an automatic way of assessing the relevance of information for the user, based on how often the user accesses it.

Exploiting the cognitive definition [28,29] of the human forgetting function (see Section 3.1.1), we can define the forgetting function for each edge $e_{ij} \in E$ of a user’s semantic network at a time $t$ as:

$$f(e_{ij}, t) = e^{-\beta_{ij}(t-t^*)} \quad (1)$$

where $t^*$ is the last time the edge $e_{ij}$ was used in exchanges with other peers (i.e. its last “activation”) and $\beta_{ij}$ is the “speed of forgetting”. This factor depends on the number of previous accesses to this edge in the past. Therefore, we can define this parameter as follows:

$$\beta_{ij} = \gamma \frac{p_{ij}'}{p_{ij}}$$

where $\gamma$ is a speed coefficient and $p_{ij}'$ is the “popularity” of $e_{ij}$ at time $t$, i.e. the number of times $e_{ij}$ has been used in the encounters happened before $t$.

At time $t_0$, when the device is activated, we have that $f(e, t_0) = 1$, $\forall e \in E$. Subsequently, whenever $f(e, t) \leq \phi_{\min}$, where $\phi_{\min}$ is a limiting threshold value, then the edge $e$ is removed (i.e. it is “forgotten”) from the semantic network. The $\phi_{\min}$ value is termed as the forget threshold.

Vertices could be also affected by the forgetting process that is acting on the edges of the semantic network. In fact, the removal of an edge $e$ may leave a vertex $v$ at one of $e$’s endpoints completely disconnected. In this case, the vertex $v$ is also deleted from the semantic network. After deletion, the only way to add again an edge or a vertex to the semantic network is to receive it during successive encounters with other nodes, which is the process we explain next Fig. 4.

4.3. Semantic knowledge dissemination

In this section, we describe how a node, when meeting another peer, is able to retrieve from its memory the most relevant semantic information to be exchanged. Essentially, the proposal hereafter describes the way in which concepts pass from person to person during conversations.
a vertex each time it is included in $K$ (lines 5–7 of Algorithm 1). Then, the computation of the contributed network can start from the set of key vertices. These vertices are first ordered according to their relevance in memory. Relevance is computed for each key vertex by summing up the weights of its incoming edges, taken as a measure of the total importance (or relevance) of that concept in the node’s semantic network (line 8 of Algorithm 1). Taking the key vertices (sorted by relevance) one at a time, edges and vertices are visited and passed from the donor network to the contributed network using Algorithm 2, that is based on fluency. In this algorithm, the fluency heuristic is applied to evaluate whether to follow an edge $e_{ij}$ or not. Fluency is a cognitive decision-making strategy that favours recognized objects (i.e. objects seen more than a given amount of times, see Section 3.2) against unrecognized items. It assumes that the former are more relevant than the latter ones, in the information selection task. Hence, we start by excluding all unrecognized edges, i.e. the edges whose popularity is below a recognition threshold $\theta_{rec}$ (line 5 of Algorithm 2).

Acting only over recognized items, fluency makes a subsequent discrimination based on the perceived speed of retrieval from memory. In order to replicate this fact in our system, we consider that the following facts affect the ease of retrieval, and, thus, the relevance, of semantic concepts during an interaction:

- the highest the recall value of an edge (i.e. it is more easy to recall it), the most relevant the edge is;
- the relevance of an edge decreases as long as we get farther from a key vertex, i.e. it is more difficult to recall it, given the actual “topics of discussion” (the key vertices);
- anyway, the longer the contact time between two nodes (i.e. the longer the discussion is), the more time is available to navigate the donor network and include edges and vertices in the contributed network, i.e. more concepts can be recalled with longer “discussions”.

In order to take all these observations into account, we compute, for each outgoing edge $e_{ij}$ of a vertex $v_i$, a “retrieval weight” quantity. This quantity is computed for an interaction that starts at a time $t$ and ends at time $t^*$. It is defined as:

$$w(e_{ij}, n, t^* - t) = f(e_{ij}, t^*) \frac{1 - e^{-\tau(t^* - t)}}{n}$$

where $f(e_{ij}, t^*)$ is the memory strength value of $e_{ij}$ at time $t^*$, $n$ is the number of hops in the shortest path to the nearest key vertex and $\tau$ is a “speed” factor that regulates the dependency of the weight on the communication duration $(t^* - t)$. The retrieval weight is taken here as a surrogate of the speed of retrieval needed by the fluency heuristic, since it favours the edges with higher strength in memory and that are more well-connected to the key vertices.

Given a vertex $v_i$, its outgoing edges are sorted with respect to their retrieval weight value (line 6). Taking them one at a time in descending order, we include the selected edge in the contributed network, and continue the donor network exploration from this connection (lines 6–13 of Algorithm 2). All the edges whose retrieval value is below a threshold $\omega_{min}$ are not considered (line 7 of Algorithm 2). Note that the strength in memory of selected edges is set to the maximum, since inclusion in the exchanged data corresponds to an “activation” in memory of those connections.

Whenever the number of vertices added to the contributed network has reached the limit of tags that can be exchanged during the contact, i.e. $|\tilde{V}| = tag\_limit$, or no other paths (i.e. edges) can be selected from the donor network, the contributed network computation ends and the resulting graph is passed to the recipient node. This peer merges the contributed network to its own network (i.e. the recipient network) by simply adding all the missing vertices and edges. This process corresponds to an enrichment of the semantic knowledge of the recipient peer in terms of both concepts (i.e. vertices) and relationships between them (i.e. edges). All the edges received from the donor network (either new or already present in the recipient network) set their weights in memory to 1, since they are “activated” by the “conversation”.

### 4.4. Semantic content dissemination

The previous selection of the most relevant semantic concepts, with respect to the current interaction, drives the next step in the data exchange process: the selection of relevant data items to exchange. In order to carry out this operation, we exploit another simple decision rule derived from the cognitive science field: the tallying heuristic. For this step, we refer to the pseudo-code given in Algorithm 3. The rationale to select data items to exchange is based on the match between their tags and the concepts that have been exchanged between the semantic networks. Intuitively, we exchange data items that have as many tags as possible within the set of concepts “used” in the “discussion” between the nodes. The tallying heuristic models exactly this behaviour. Given a set of cues of cardinality $m$ (which in our case is the set of tags exchanged during the contact as explained in Section 4.3), data items are ranked based on the number of favourable cues they possess. Therefore, we rank data items for possible exchange based on the cardinality of the intersection between the cues and the tags associated to them (lines 5–7).

We also consider that the other party sends to the node the list of the IDs of the items it already owns. Thus, those data items can be directly pruned out from the selection process (line 4). Moreover, like for the exchange of semantic concepts, we assume that there is a maximum number of exchangeable data items data\_limit. Thus, once the data items have been ranked according to tallying, the first data\_limit ones are selected to be passed to the other interacting peer (lines 8 and 9).

Note that the chosen “cues” used by our version of tallying are regarded as relevant since they derive from a previous decision-making cognitive process that is pertinent with the actual contact. Moreover, the number and identity of these cues vary from one encounter to the other, reflecting the peculiarity of each separate meeting and the changes made by previously experienced contacts in the environment.

An example of the tallying heuristic applied to the data items selection problem is shown in Fig. 5. In this figure, we have two data items (two pictures) along with their own semantic descriptions and an already computed contributed network. Since the cardinality of the intersection of the semantic description of the first picture is greater than that of the second picture (2 vs. 1), the first picture is selected for being exchanged.

---

**Algorithm 3** Tallying algorithm.

1. Let $\tilde{V}$ be the nodes of the contributed network;
2. Let $I$ be the set of data items of the node;
3. Let $I'$ be the data items owned by the other peer;
4. Let $I'' = I - I'$;
5. for each $i \in I''$ do
6.   Let $\text{tall}(i) = |\text{semanticDesc}(i) \cap \tilde{V}|$
7. end for
8. Rank $I''$ in descending order according to the $\text{tall}$ values
9. Send the first data\_limit items of $I''$ to the other node

---

3 This corresponds to a depth first visit, as discussed in Section 3.1.
5. Experimental results

In this section, we analyse the performance of our solution through a set of experiments performed in synthetic scenarios. Precisely, we test our approach against an alternative solution, comparing both approaches in terms of knowledge and content dissemination effectiveness, whereby, by knowledge dissemination we mean how concepts spread from node’s to node’s semantic network. We analyse and compare the structural properties of the nodes’ semantic networks built according to the two approaches and, finally, we provide a sensitivity analysis of our approach.

5.1. Simulation settings

5.1.1. Synthetic mobility scenarios

Mobility traces are generated by HCMM [22], a well-known mobility model already used in several papers in the literature to evaluate data forwarding and data dissemination algorithms for opportunistic networks. HCMM incorporates temporal, social and spacial notions in order to obtain a proper representation of real users movements [47]. In HCMM the simulation area is organised as a rectangular grid, where a single grid cell represents the physical location of a community of nodes. In each community two kinds of mobile nodes are allowed: travellers and non-travellers. Non-travellers roam only inside their community, while travellers, according to a given probability distribution, from time to time visit other social communities different from the one they belong to. When moving inside a community, for each simulated time step, each node (both travellers and non-travellers) randomly select a velocity and a new position to reach inside the community area. Velocity and position are selected according to uniform probabilities (for velocity, inside a given velocity range). In this context, the only way to exchange information is by means of nodes mobility, and travellers play an important role because they are the unique bridge between communities (besides possible border effects between nodes of adjacent communities).

In this paper we considered three different mobility scenarios. Precisely, in Scenario 1 there are 99 mobile nodes moving in a 1km$^2$ area and grouped in a single social community. In Scenario 2 we consider a less crowded configuration. In the same simulation area (1000 m × 1000 m) as for Scenario 1, we have only 50 mobile nodes roaming in a single social community. Finally, in Scenario 3, 99 nodes are divided in three physically separated groups (33 nodes for each group) representing three different social communities. Nodes move in an area of 1km$^2$ divided in a 6 × 6 grid, and communities are placed far from each other so to avoid any border effect. Details on configuration parameters for the scenarios can be found in Table 1.

5.1.2. Dataset description

Data assigned to the nodes is selected from the CoPhIR dataset [48]. This dataset is made up of more than 100M images coming from Flickr. For each user’s image, the list of associated tags is available. To test our solution, we created two datasets, D1 and D2, according to the following procedure.

In D1, images were selected in order to have the initial users’ semantic knowledge strongly clustered around three main concepts poorly connected to each other. Specifically, a main concept is a hashtag containing a very common word representing a very general category of pictures, e.g. “mountain”, “sea”, “lake”. In this case, selected images have from 2 to 4 tags and only one of the three main concepts. Fig. 6a represents the entire knowledge present in the network at the beginning of each simulation, i.e. the graph of the union of all nodes’ initial semantic networks. The resulting graph G1 is made by 221 vertexes and 455 edges. This dataset represents a sort of a controlled environment we used to perform a first evaluation on the performance of our approach, while the rest of investigations have been made on the more complex dataset D2, hereafter described.

D2 represents a more real situation in which the resulting graph built from the union of all nodes’ initial semantic networks has a more complex structure. Images in D2 have from 10 to 15 tags each and no other constraints to drive the images selection have been considered (as we did for D1). Fig. 6b shows the entire knowledge present in the network at the beginning of each simulation. The resulting graph G2 is made by 1302 vertexes and 8845 edges. In Table 2 more details about both G1 and G2 are reported. We pointed our attention on such initial configurations in order to both study the ability of each user to retrieve the information semantically related to its initial interests and to analyse the overall permeation of data in the network. Note that the interests of the users are automatically defined by the tags in their local semantic networks. Initially, they are thus defined by the tags of the locally

![Fig. 5. Example of tallying heuristic applied to the semantic content exchange process.](image-url)
available pictures, and evolve over time based on the diffusion of tags due to the algorithms presented in Section 4.

5.1.3. Performance evaluation indexes
We observed and studied the evolution of the knowledge and content acquisition processes generated by the interactions between users. We defined two indexes to measure the knowledge and content dissemination performance, respectively. Moreover, we used the F-measure [49], a commonly used metric in the field of information retrieval, to evaluate the relation – in terms of accuracy – between the knowledge acquired and the contents retrieved by nodes, during the simulation (a more formal definition of the F-measure is provided in Eq. (7)). In Table 3 we provide the notation we use to define the above mentioned indexes.

We measure the Knowledge Dissemination (KD) by computing how much of the starting global knowledge reaches nodes at the end of the simulation. The KD index is defined in Eq. (3).

\[
KD = \frac{1}{|N|} \sum_{n \in N} \frac{|V_n|}{|V_c|}
\]

KD in Eq. (3) measures the average (over all nodes) percentage of the entire knowledge that is available at nodes at the end of the simulations. Reaching a KD in the range of 100% would mean that all semantic data reach all nodes. Given the structure of the initial overall semantic network and the knowledge acquisition process we don’t expect to reach 100% for this index. Precisely, in our system, users acquire only the information semantically correlated to their knowledge, while throwing out less relevant concepts. This triggers a filtering process that generally prevents users from collecting all the existing concepts in the environment.

We also define a second measure, the coverage, as the fraction of items owned by a node over all the items that contain a tag matching one of the concepts in its semantic network. This index is defined in Eq. (4). Precisely, for a given node \( n \) and a given tag \( v \) in its SN we calculate the ratio between the number of contents owned by the node having \( v \) in their semantic description, over the number of all contents in the system whose semantic description contains \( v \) (part B of (4)). Then we average over all the tags in the node’s SN and over all nodes in the system (part A of (4)).

\[
\text{CGV} = \frac{1}{|N|} \sum_{n \in N} \frac{1}{|V_n|} \sum_{v \in V_n} \frac{1}{|D_v|} \sum_{c \in C_v} \frac{|\sum_{C_v} T_c \cap V_n|}{|V_n|}
\]

For this index an ideal dissemination system would reach 100%, as this means that users receive all the data items related to concepts they have in their semantic network.

Finally, in order to evaluate the accuracy of the semantic information acquired with respect to the contents retrieved, we used the F-measure. It is made of two indexes called precision and recall denoted by \( p \) and \( r \), respectively. In our setup the precision index (between 0 and 1) measures how appropriate are the contents retrieved by a node with respect to its semantic network. For a given node \( n \) the precision is defined as follows:

\[
p_n = \frac{|\bigcup_{c \in C_v} T_c \cap V_n|}{|\bigcup_{c \in C_v} T_c|}
\]

The recall index (between 0 and 1) measures how appropriate is the node’s semantic network with respect to the contents it has collected during the simulation. For a given node \( n \) the recall is defined as follows:

\[
r_n = \frac{|\bigcup_{c \in C_v} T_c \cap V_n|}{|V_n|}
\]

![Initial knowledge graphs (namely G1 (a) and G2 (b)) defined as the union of all nodes’ semantic networks at the beginning of the simulation for dataset D1 (a) and D2 (b).](image-url)
In our context, precision equal to 1 means that there are no tags associated to content node \( n \) that are not in its semantic network (or, in other words, that all retrieved content are associated to tags “known” by the node). Recall equal to 1 means that for each tag in the semantic network there is at least one retrieved content associated to that tag. The \( F \)-measure for a single node \( n \) is defined as:

\[
F_n = 2 \frac{p_n * r_n}{p_n + r_n}
\]  

(7)

Finally, we considered the average \( F \)-measure over all nodes:

\[
\overline{F} = \frac{1}{|N|} \sum_{v \in N} F_v
\]  

(8)

Note that \( F_n \) is between 0 and 1, and if it is higher the more recall and precision are both high and close to each other. Therefore it measures how good a retrieval system is from both the precision and recall standpoints.

5.1.4. Benchmark algorithm description

To best of our knowledge, there are no other solutions in literature taking into account the problem of disseminating both semantic knowledge and contents in opportunistic networks. Therefore, we defined an alternative dissemination algorithm that shares the general characteristics of our approach – the semantic edge is organised in semantic networks, and nodes exchange both semantic information and contents – but the rules according to which nodes exchange semantic information and contents are driven by a pure random process.

Regarding the exchange of semantic knowledge, as in the cognitive approach, nodes populate the respective contributed networks from a vertex they have in common but, differently from the cognitive approach, they continue appending semantic concepts to the contributed network by navigating their semantic network according to a random walk. Namely, the next vertex to be appended to the contributed network is selected with probability \( 1/k \) where \( k \) is the out degree of the current vertex of the node’s semantic network. The selection of the contents to be exchanged with the other peer is random, as well. Each node uniformly selects data_limit contents choosing between those having at least one tag (in their semantic description) in common with the contributed network.

By comparing our cognitive approach with this benchmark, we aim at investigating the impact on the dissemination process (both for semantic information and data items) deriving from the use of a structured and well defined information selection process driven by cognitive models (in particular, cognitive heuristics) against one where semantic information is also organised in an associative network, but the choice of the information and contents to exchange is not driven by cognitive models. The selection policy used by the benchmark is the simplest one that could be devised. Note, however, that such uniform random policies may perform quite well in homogeneous mobility cases, such as Scenarios 1 and 2 in our case. For example, this has been found to be the best policy for topic-based data dissemination in opportunistic networks in homogeneous mobility settings [33,34].

Results reported in the following simulations are the statistics collected on 10 different tests obtained from 10 different mobility traces of the HCMM model and averaged across all nodes. Each experiment is a transient simulation ran for 25000 s. In the rest of this section, we use some conventions in order to make the values of the forget and retrieval thresholds more intuitive for the reader. Remember that the forget threshold (see Section 4.2) defines a weight value under which edges are dropped from a semantic network, while the retrieval weight threshold (see Section 4.3) sets the limiting weight under which edges are not considered for inclusion in a donor network during an exchange. In the following, we define these two parameters with respect to the time passed since the last usage of an edge in an exchange. The longer this time, the lower the relevance of that edge in a node’s memory. Therefore, it is more difficult to remember that edge (i.e., include it in exchanges) and it becomes more likely to forget about it. In the rest of this section, a notation like \( f_{\text{min}} = 50 \)s means that the forget threshold \( f_{\text{min}} \) is set in such a way that edges with popularity 1 are dropped from a SN in case they are not seen before 50s from the last time they were used in an exchange. Using this notation, we have that the higher \( f_{\text{min}} \), the longer an edge is retained in the SN. On the other hand, a notation like \( W_{\text{min}} = 25 \)s means that the retrieval value \( W_{\text{min}} \) is computed taking into account, as a reference case, an interaction between nodes of 2s, that allows nodes to include (warm up) at least edges at distance 1 from a key concept if they are not used (i.e., they were subject to the forget process) from no more than 25s. The higher \( W_{\text{min}} \), the higher the number of edges that are “warmed up”, and, as a consequence, the higher the number of vertices that could be included in a contributed network.

5.2. Overview on the key findings

For the sake of presentation clarity, in this section we summarise and anticipate the key findings we draw from our experimental results, providing, for each one, the pointer to the section where it is presented and explained in more detail. We found that using cognitive-based algorithms to represent dynamically varying users’ interests, that in turn drives the dissemination of available data, has multiple advantages over a benchmark solution that is not based on human cognitive models. Specifically:

- Nodes in the network are able to recognise and select the most relevant information available in the environment; moreover the representation of the semantic information collected from the environment is very stable, i.e. the most relevant information last in the nodes’ memory for long time, thanks for reinforcement from frequent accesses. See Section 5.3;
- The Knowledge Dissemination triggered by our cognitive approach drives a more efficient content dissemination with respect to the benchmark. See Section 5.3.4;
- The internal structure of the local semantic information collected by nodes is representative of the entire semantic information present in the environment, i.e. the graph properties of the semantic information representation in nodes’ internal memory are very close to the properties of the complete semantic network graph. See Section 5.4;
- The cognitive mechanism of information selection and representation combined with the corresponding data dissemination algorithm proves to be efficient in terms of memory occupation. In fact, in Section 5.5 we show that even increasing the resources involved in the dissemination process (memory for tags and data items), we obtain only a marginal increase of performance, meaning that limiting memory resources does not drastically degrade the overall performance of the system.

5.3. Performance analysis of information-dissemination algorithms

In this section we provide a comparison of the proposed solution against the benchmark approach, in all scenarios previously described. For the sake of simplicity, from now on the acronyms CA and BA we will refer to the cognitive approach and the benchmark approach, respectively.

We compare the two approaches using the Knowledge Dissemination (KD), F-Measure and Coverage metrics. All the results reported in this section are obtained by varying the \( f_{\text{min}} \) threshold between 150 and 300 s. For all the other parameters, we use the values reported in Table 4. Unless otherwise stated, the x axis is plotted in log-scale.
5.3.1. Scenario 1

The tests reported in Figs. 7–9 are obtained using D1. Fig. 7 shows the results obtained with $f_{\text{min}} = 150 s$, and in Fig. 8 plots the results obtained with $f_{\text{min}} = 300 s$. In both these figures, the left side shows the variation over time of Knowledge Dissemination, while the right side depicts the variation of the F-measure associated to the data dissemination process.

In both the cases presented in the figures, we can note that the F-measure of the CA approach initially decreases, reaching a minimum, and successively starts to increase. On the contrary, the same metric always decreases for the BA solution. This is due to the fact that there is some kind of inertia in the spreading of data items with respect to the diffusion of tags. In fact, semantic knowledge (i.e., tags) is spread first, while data items are “pulled” toward interested nodes as a side effect. For the CA approach, there is a transient moment where nodes start to increase their knowledge faster than they exchange correlated data items, leading to a decrease in the F-measure value. Initially, this consideration holds also for the BA approach. However, as a consequence of the forgetting process, BA soon starts to lose relevant semantic information, as can be seen by the KD values (discussed later in this section). As a result, the F-measure continues to decrease at a speed that is proportional to the deletion of semantic concepts.

Looking at the KD metric, it is possible to note that for BA it initially shows a rapid growth, compared to that of CA. However, as we already observe, when the simulation proceeds, BA is not able to sustain this growth. On the contrary, it enters a sort of “forgetting” phase, where the semantic information gradually gets lost. This phase is reflected also in the quality of the data dissemination process. With the lowest $f_{\text{min}}$ value, the KD metric for the BA solution reaches 0, meaning that all the information has been deleted from all the semantic networks in all the runs of the experiment.

The divergence between the behaviour of the two systems can be explained by the differences in the contributed network computation mechanisms. BA does not give any particular preference to the edges used to explore the donor network when computing the contributed network. In this way, it is easier to have a greater variety in the content of contributed networks exchanged over time. As a consequence, at the beginning the KD experiences a steep increase. On the other hand, the cognitive-based solution proceeds more slowly. First of all, an edge becomes eligible to be added to the contributed network only when recognized. Moreover, among recognized edges, the ones that connect semantic concepts that are closer to a key vertex are preferred to the ones that connect more distant concepts. This mechanism leads to the creation of a

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$W_{\text{max}}$</td>
<td>35 s</td>
</tr>
<tr>
<td>tag_limit</td>
<td>25</td>
</tr>
<tr>
<td>data_limit</td>
<td>10</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>a</th>
<th>a</th>
</tr>
</thead>
<tbody>
<tr>
<td>b</td>
<td>b</td>
</tr>
</tbody>
</table>

![Fig. 7. KD(a) and F-measure(b) comparison with $f_{\text{min}} = 150 s$ on dataset D1 (Scenario 1).](image)

![Fig. 8. KD(a) and F-measure(b) comparison with $f_{\text{min}} = 300 s$ on dataset D1 (Scenario 1).](image)
sort of “core” of semantic information (vertices and edges) inside each semantic network. This “core” is increasingly reinforced over time and allows other, new concepts to be gradually included in it, giving a more clear structure to the semantic network.

In front of these two different approaches for growing the semantic networks, the underlying forgetting process is more likely to have detrimental effects on the semantic networks of BA, rather than on those of CA. In fact, in the former case there is no particular mechanism for selecting the path to follow in the donor network, and the dimension of the semantic network increases rapidly. As a consequence, a relevant number of edges could remain not visited for a long time, leaving space for the forgetting process to delete them. As a further consequence, the vertices attached to them could also be eligible for removal, thus leading to a loss of information.

This situation can be better viewed by analysing the variations over time of the mean weight of the edges in all the semantic networks of the system. Fig. 9 presents this data for both $f_{\text{min}} = 150$ and $f_{\text{min}} = 300$. Initially, the mean edge weight starts to decrease for both BA and CA. This is due to the fact that edges need to start being exchanged in order to increment their weights. To this end, in CA edges must also become recognised. After having reached a minimum, the mean weight of the edges in the cognitive-based solution starts to rapidly increase. This is an indication of the reinforcement of the information (and, thus, the weights of the edges) in the semantic networks around a “stable core”. The increment in the mean edge weight means that edges cannot generally be deleted by the forget process, since their weights are far above the forget threshold.

On the other hand, the mean edge weight in BA simply diminishes its decreasing rate, until it starts to fluctuate around a stabilisation value. This value is low, highlighting the fact that, on average, the semantic networks built using BA are “weak”. In fact, due to their low weight value, edges can be more subject to be forgotten.

5.3.2. Scenario 2

In order to further analyse the behaviour of the two approaches, we now show results obtained using dataset D2. Figs. 10 and 11 refer to the single-community scenario defined in Scenario 2.

In both these cases, it is possible to note the same effects observed with dataset D1. The F-measure of the CA approach initially decreases. After this phase, the semantic knowledge owned by each device starts to attract more and more related data items, leading to an increase of the F-measure metric. For BA, the starting delay on data dissemination is successively worsened by the lost of semantic information, leading to a continuous decrease of F-measure values.

With respect to the KD metric, BA shows an initial faster growth of the semantic networks, but it is not able to preserve
the retrieved information over time. With \( f_{\text{min}} = 150 \)s (Fig. 10), BA reaches KD = 0, and also with \( f_{\text{min}} = 300 \)s (Fig. 11) it gets close to this value. In all these cases, CA proceeds initially slower, allowing its semantic networks to strengthen their structure, finally achieving high values of KD.

The difference in the knowledge acquisition process are also reflected in quality of the retrieved data. This measure is also affected by the approach used by BA to select the data to be exchanged upon contact. Note that, with \( f_{\text{min}} = 150 \)s, the BA approach is never able to achieve better values of the F-measure than CA. With \( f_{\text{min}} = 300 \)s, BA only shortly has a F-measure better than CA, eventually declining the values of this metric, in parallel with the loss of semantic knowledge.

5.3.3. Scenario 3

In the last scenario, we tested the two competing approaches in a more complex situation. Nodes are divided into three separate communities, and are equipped with data coming from the D1 dataset. Non-travelling nodes have to rely on travellers to collect both knowledge and data spread in the other communities. Fig. 12 shows the variation of KD and F-measure with \( f_{\text{min}} = 150 \)s. In this case, the usual initial advantage of BA over CA in the KD metric lasts for a very short time. In the F-measure metric, BA starts to decline, without ever stopping.

With \( f_{\text{min}} = 300 \)s, BA shows an increased ability to preserve the content of the semantic networks of the system. However, BA eventually enters a declining phase, although this process is slower than in all the previous cases. In order to better investigate the behaviour of BA (and CA) in this case, we allowed the simulation to run longer, i.e. for 125,000 s. It is possible to observe that the declining phase of the BA curve leads the CA solution to outperform BA, as in all the other cases. This fact can be observed for the F-measure, too. Initially, BA has a better performance, but it finally starts decreasing. At the same time, the F-measure curve of CA increases, and CA ends the simulation with a better performance than BA.

5.3.4. Coverage

Table 5 presents the performance under all the scenarios of both CA and BA with respect to the Coverage metric. The table reports the values and the time instants at which Coverage

![Image of graphs](image-url)

**Fig. 11.** KD(a) and F-measure(b) comparison with \( f_{\text{min}} = 300 \)s on dataset D2 (Scenario 2).

![Image of graphs](image-url)

**Fig. 12.** KD(a) and F-measure(b) comparison with \( f_{\text{min}} = 150 \)s on dataset D1 (Scenario 3).

**Table 5** Coverage values and times for the Coverage metric in all the considered scenarios.

<table>
<thead>
<tr>
<th>( f_{\text{min}} )</th>
<th>Scen. 1</th>
<th>Scen. 2</th>
<th>Scen. 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CVG</td>
<td>t</td>
<td>CVG</td>
</tr>
<tr>
<td>CA</td>
<td>150</td>
<td>0.987</td>
<td>2105</td>
</tr>
<tr>
<td></td>
<td>300</td>
<td>0.989</td>
<td>2160</td>
</tr>
<tr>
<td>BA</td>
<td>150</td>
<td>0.0</td>
<td>23255</td>
</tr>
<tr>
<td></td>
<td>300</td>
<td>0.599</td>
<td>24970</td>
</tr>
</tbody>
</table>

The values of Coverage for both CA and BA are reported in Table 5. The table shows that BA has a better performance than CA in all the scenarios considered. However, the time instants at which Coverage is reached are different for each scenario. In scenario 1, BA reaches a higher Coverage value than CA, while in scenarios 2 and 3, CA has a better performance. The time instants at which Coverage is reached are also different for each scenario and for each approach.
stabilises. Specifically, convergence is defined as the point in time, during a simulation, when the coverage value does not change any more until the end of the simulation. Note that, as data items are not dropped by nodes and no new data items are generated during simulations, coverage can only increase. It stops increasing, and therefore remains constant, when the dissemination process becomes stable and nodes do not exchange any more data items during contacts. Consequently, according to this very strict definition of coverage, convergence times may appear quite high. However we decided to use this definition because we are interested in studying the performance of our system when the dissemination process enters in steady state.

Generally, in almost all the cases, convergence is reached by CA faster, and with higher Coverage values, than BA. In particular, it is possible to note that, for $f_{\text{min}} = 150s$, BA ends up with a Coverage of 0. This is due to the deletion of all the semantic concepts from the nodes’ semantic networks, as already observed in all the previous experiments. In only one case, for $f_{\text{min}} = 300s$ under Scenario 2, BA is able to reach convergence faster than CA. In this case, the $f_{\text{min}}$ value gives time to BA to rapidly accumulate a high number of data items. Given the fact that data items are never discarded once acquired, the definition of the Coverage measure (see Formula 4) implies that the Coverage value could remain high even when the semantic knowledge starts to decrease, due to forgetting. However, all the other metrics (see Fig. 11) highlight the fact the performance of the system is degrading. From these observations, we can reasonably suppose that also in this case the Coverage metric will start to decrease, possibly reaching 0.

As a general remark on these results, we can note that CA achieves good Coverage values even with a low $f_{\text{min}}$. This implies that, even in face of a limited resource consumption (low $f_{\text{min}}$), CA is able to let relevant data items flow toward interested nodes in the system (Fig. 13).

5.4. Analysis on node’s semantic networks

Next, we analyse in more detail the nodes’ semantic networks for both the approaches. For the sake of simplicity, the results presented hereafter will refer to a tagged node that we can consider, without loss of generality, as representative of all the other nodes in the system. Specifically, for Scenarios like 1 or 2 this is any of the nodes in the only existing community. For Scenario 3, we consider one of the non-traveller nodes.

We tracked the state of the tagged node’s SN at successive time instants. Figs. 14 and 15 refer to the SN evolution in CA and BA, respectively. We can again observe the different growth rate of the SN triggered by the two approaches. With CA, the tagged node’s SN grows more slowly than with BA, however this leads to a more robust SN evolution than with BA. If we compare the state of the SNs at 700s we notice that the structure of the SN built by CA is more similar to C1 than the one built according to BA. Moreover, despite the faster initial knowledge acquisition of BA, the randomness of
the mechanism leads to a more chaotic SN structure, characterised by long and weak paths between vertexes. This behaviour makes the resulting SN very unstable and more susceptible to the forgetting process. For example, when using BA, after 2475s all the semantic information in the SN has been lost. Conversely, thanks to the cognitive process, CA tends to attach the new information around an increasingly stable core. The very same behaviour can be also observed in the multi-community environment of Scenario 3, as shown in Fig. 16. The upper part of the figure reports the final configuration of the SNs of three tagged nodes (one per community) using CA. The other half of the figure presents the configurations of the SNs of the 3 tagged nodes when the BA scheme is used. The latter configurations are taken just before the SNs of each node become empty, due to the forgetting process.

Also in this case, the cognitive mechanisms of the CA scheme lead the SN structure to be very similar to G1. It is worth noting that no node in the system knows the real structure of G1, but nevertheless, they are able to replicate a structure very similar to the global one, that could be in principle obtained only with global knowledge. Another key feature of CA is that at the end of the simulation, all nodes’ SN are very similar. This can be seen as some kind of a spontaneous consensus. That is, in a closed environment where no new information is generated and when information can eventually circulate across all nodes, knowledge tend to become homogeneous among nodes, which align towards a common representation of available semantic information.

This kind of similarity is reflected by structural properties of the nodes’ SNs. We averaged over 10 simulated experiments the tagged node’s final semantic network size for both CA and BA and compared it with the complete sizes of the graphs (G1 and G2). Table 6 shows the number of vertices and edges in the final SN of the tagged node as a fraction of those in the global graphs. Diameter values are absolute. In this case, diameters of G1 and G2 are 4 and 8, respectively. As reported in the table, though the SN formed with CA is smaller than the corresponding global graph, it approximates very well the diameters of the global graphs. On the other hand, BA is not as accurate as CA. Most of the time BA is not able to preserve the information in the SN until the end of simulation. Only when the forgetting time is sufficiently high the information lasts until the end (Scenario 2 and 3 with $f_{max} = 300$) and even in that case the graph properties are not always respected (e.g., see the much different diameter values).

![Fig. 15. Evolution of a tagged node's semantic network evolution running BA in Scenario 1.](image1)

![Fig. 16. Final configuration of three tagged nodes' SNs running CA (upper half) and BA (lower half) in Scenario 3.](image2)
Table 6
Node’s final semantic network properties for CA and BA. Mean values and standard deviations computed on 10 runs are reported. Missing values (“−”) means that nodes’ semantic network are empty, as a consequence of the forgetting process.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>( f_{\text{min}} )</th>
<th>CA</th>
<th>BA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>% Edges</td>
<td>% Vertex</td>
<td>Diameter</td>
</tr>
<tr>
<td>1</td>
<td>150</td>
<td>38.5 ± 3.9</td>
<td>71.3 ± 6</td>
</tr>
<tr>
<td>2</td>
<td>300</td>
<td>39.7 ± 5.9</td>
<td>59 ± 6.7</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>9.6 ± 2.3</td>
<td>22.7 ± 4.9</td>
</tr>
</tbody>
</table>

Table 7
Cramer von Mises goodness of fit test computed on the degree distribution of a tagged node semantic networks obtained with CA and BA. Results have been computed on 10 runs. R and NR mean “Reject” and “Do not reject”, respectively.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>( f_{\text{min}} )</th>
<th>CA</th>
<th>BA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>150</td>
<td>0.6225</td>
<td>0.01970</td>
</tr>
<tr>
<td>2</td>
<td>300</td>
<td>0.3925</td>
<td>0.0756</td>
</tr>
<tr>
<td>2</td>
<td>150</td>
<td>0.0679606</td>
<td>0.764137</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>0.157223</td>
<td>0.368298</td>
</tr>
<tr>
<td>3</td>
<td>150</td>
<td>0.385</td>
<td>0.0791754</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>0.2325</td>
<td>0.212442</td>
</tr>
</tbody>
</table>

Fig. 17. CCDFs of the degree distribution for CA and BA (solid curves) compared with the degree distribution of G2 (dashed curve).

In order to deeply investigate the similarity between the final SN generated by CA and BA, and the original graphs G1 and G2, we analyse the vertex degree distribution of the SNs. Namely, we compared the empirical vertex degree distribution of the node’s final SN obtained with CA and BA with the empirical distribution of G1 and G2. We used the Cramer-von-Mises goodness of fit test with a significance level of 95% to compare the distributions. Results are reported in Table 7.

As we can see, in almost all the experiments the empirical degree distribution of node’s SN using CA is the same as that of the global graphs. Differently, BA only in one case was able to reproduce a structure similar to the original graph. As an example, Fig. 17a and b show the comparison between the CCDF of the degree distribution of the final SN with the one of G2 (Scenario 2, \( f_{\text{min}} = 300 \)), both for CA and BA. We point out that for CA the degree distribution of nodes’ SN is equivalent to the global graph, up to a constant shift.

5.5. Sensitivity analysis

Having compared in detail CA and BA, in this section we analyse the impact of the CA parameters on its behaviour. The following results are obtained under the conditions of Scenario 1.

In Fig. 18 we show how the KD metric varies by using three different settings of the forget threshold value. As expected, higher values of \( f_{\text{min}} \) (i.e. edges are “remembered” for longer times) allow the system to achieve higher values of KD. In fact, less popular
threshold below the one marking the phase transition, also CA looses information faster than it can consolidate it. Beyond this value, information has enough time to consolidate in the semantic networks, and does not disappear from the network.

Fig. 19 presents the performance of the system with different values of the \( W_{min} \) threshold (remember that the higher \( W_{min} \) the more edges can be included in the semantic network exploration process between two nodes during a contact). Also in this case, higher values of the threshold allow the system to achieve higher values of KD. However, there is a sort of marginal utility gain in increasing the value of \( W_{min} \), which means that increasing the size of the semantic network explored during a contact is not worth after a certain point.

Fig. 20 shows how the KD metric changes in front of different values of tag limit, which sets the maximum number of SN tags exchanged during a contact. The inclusion of more vertices in a contributed network leads to a significant increase of KD. Therefore, the setting of this parameter should be carefully evaluated, as increasing it also means increasing the amount of traffic exchanged during contacts. However, again we can notice that the increase in KD is not proportional to the increase tag limit, which suggests a marginal utility law also in this case.

Finally, Fig. 21 presents the impact on the content dissemination process of various data limit values, which limit the number of content items exchanged during a contact. In particular, Fig. 21a presents the impact of this parameter on F-measure, while Fig. 21b shows its impact on Coverage. Note that an increase in the number of items exchanged during contacts does not seem to particularly affect the value of the F-measure. This can be explained by looking at how this metric is computed. One of the main contributions in the computation of the F-measure value is given by the intersection of all the semantic concepts that describe the received data items and the semantic concepts stored on the semantic network of a node. Exchanging more items during contacts could not lead to increase of the this quantity. In fact, the items that maximise the intersection described above are likely to be the first ones in the set considered for exchange, because they are those most correlated with the concepts exchanged during the same contact. Therefore, they could be always present, even with the smallest amount of exchanged items (i.e. data limit = 5 in our case).

On the other hand, when nodes can exchange (and, thus, also receive) more data items at each encounter, they can more rapidly collect all the items that are described by the tags they carry in their semantic networks. Therefore, the Coverage measure achieves higher values, and converges more rapidly, when data limit is set to higher values. Moreover, also in this case we can notice a...
marginal utility behavior. In fact, even increasing the resources involved in the dissemination process, we obtain only a marginal increase of performance. This means that we can save the resources of mobile devices without degrading significantly the overall performance of the system.

6. Conclusion

In this paper we presented a set of algorithms enabling nodes belonging to an opportunistic network to disseminate autonomously both content items and semantic information associated to them. With respect to the work present in the literature we are able to represent interests of users in a more flexible way with respect, for example, to conventional topic-based schemes. Here, we consider that users’ interests can change over time, as a result of a knowledge acquisition process that is also the effect of social interactions between them. In a scenario of cyber-physical convergence, where users’ devices are the main tools through which users acquire knowledge and content from both the physical and the cyber environment, this is important, because devices should act as much as possible as proxies of the users in the cyber world, and therefore behave as closely as possible as their users would behave in the same conditions. To this end, we based our solution on well established models coming from the cognitive science field. Namely, we exploited the associative network memory model to build a representation of the semantic knowledge on which we run two fast and frugal decision making strategies, i.e. Fluency and Tallying Heuristics, in order to identify which semantic data and data items to exchange between nodes upon contacts. Our simulation results demonstrate how the proposed cognitive solution can be a valuable approach to disseminate contents in an opportunistic network. We compared the performance of our approach with an alternative that does not exploit cognitive models. Interestingly, benefits are manifold. First, the proposed cognitive solution is able to build a more stable representation of the semantic information present in the environment. This means that mobile devices spontaneously select the “hot” information available in the system during time and organise it in a robust structure permitting its lasting permanence in their memory. Second, nodes’ internal semantic knowledge representation approximates very well, though at a reduced scale, the structural properties of the whole knowledge present in the environment. Indeed, the SN locally built by each node with our cognitive mechanism have a very similar degree distribution with respect to the graph representing the entire knowledge present in the environment. Finally, our results show that the cognitive approach achieves a more accurate retrieval of contents. In fact, our system does not loose the acquired information about the “hot” topics present in the environment and is thus able to disseminate those contents that become interesting over time, always keeping high levels of coverage. Therefore, with our approach personal users devices are able to properly adapt to the dynamic change of interests always providing to their users the contents they need.

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References


[20] Opportunistic networks


