Unveiling Contextual Similarity of Things via Mining Human-Thing Interactions in the Internet of Things

Lina Yao, The University of New South Wales
Quan Z. Sheng, The University of Adelaide
Anne H.H. Ngu, The Texas State University
Byron J. Gao, The Texas State University
Boualem Benatallah, The University of New South Wales
Xue Li, The University of Queensland

With recent advances in radio-frequency identification (RFID), wireless sensor networks, and Web services, physical things are becoming an integral part of the emerging ubiquitous Web. Finding correlations of ubiquitous things is a crucial prerequisite for many important applications such as things search, discovery, classification, recommendation, and composition. This article presents DisCor-T, a novel graph-based method for discovering underlying connections of things via mining the rich content embodied in human-thing interactions in terms of user, temporal and spatial information. We model these various information using two graphs, namely spatio-temporal graph and social graph. Then, random walk with restart (RWR) is applied to find proximities among things, and a relational graph of things (RGT) indicating implicit correlations of things is learned. The correlation analysis lays a solid foundation contributing to improved effectiveness in things management. To demonstrate the utility, we develop a flexible feature-based classification framework on top of RGT and perform a systematic case study. Our evaluation exhibits the strength and feasibility of the proposed approach.

Categories and Subject Descriptors: H.3.5 [Information Storage and Retrieval]: Online Information Services; H.4.0 [Information Systems]: General

General Terms: Design, Algorithms, Experimentation

Additional Key Words and Phrases: Internet of Things, correlation discovery, random walk with restart

ACM Reference Format:
ACM V, N, Article A (January YYYY), 24 pages.
DOI: http://dx.doi.org/10.1145/0000000.0000000

1. INTRODUCTION

About two decades after Mark Weiser published his seminal article [Weiser 1991], we are one step closer to his vision of ubiquitous computing, where computing power becomes invisibly integrated into the world around us and is accessed through intelligent interfaces. The main driver lies in recent advances in identification technologies such as radio frequency identification (RFID), wireless sensors, and nanotechnology, which make processing power available in smaller and smaller packages that can interact and connect. Indeed, our world is gradually evolving into an environment where everyday objects such as buildings, sidewalks, and commodities are readable, recognizable, addressable, and even controllable [Sheng et al. 2010] through the Internet.

While such a ubiquitous environment offers the capability of integrating information from both the physical world and the virtual one leading to tremendous business
opportunities (e.g., efficient supply chains, independent living of elderly persons, and improved environmental monitoring), it also presents significant challenges [Perscha 2012]. With many things connected and interacted over the Internet, there is an urgent need to efficiently index, organize, and manage these things for object search, recommendation, and mash-up, and effectively reveal interesting patterns from things.

Before effectively and efficiently classifying, managing and recommending ubiquitous things, a fundamental task is to discover relations among things. Indeed, finding things correlations is a much more challenging task than finding relations for documents, web pages or images, due to the following unique characteristics of things on the Web. However, finding things implicit relations (e.g., explicit relations can be characterized by using keyword-based textual-level similarity) underlying similarity still remains a challenge due to the specific natures of smart things in ubiquitous computing environment, we summarized three obstacles as follows:

— **Lack of uniform features.** Things are diverse and heterogeneous in terms of functionality, access methods or descriptions. Some things have meaningful descriptions while many others do not [Christophe et al. 2011a; Yao et al. 2013]. As a result, it is quite challenging to discover the implicit relationships among heterogeneous things. Things cannot be easily represented in a meaningful feature space. They usually only have very short textual descriptions and lack a uniform way of describing the properties and the services they offer [Kindberg et al. 2002].

— **Lack of structural interconnections.** Correlations among things are not obvious and are difficult to discover. Unlike social networks of people, where users have observable links and connections, things often exist in isolated settings and the explicit interconnections between them are typically limited. High level structural interconnections, this kind of information are implicit in general [Yao and Sheng 2012].

— **Contextual uncertainty.** As things are tightly bound to contextual information and very closely with people behavior, as they are functionality-oriented services. For example, such as location, are often moving from one context to another, and have no obvious easily indexable properties, such as human-readable text in the case of documents [Guinard et al. 2011; Yao et al. 2014]. Information carried by contexts for things plays more essential role in searching a ubiquitous environment compared with traditional searching.

There are much work have proposed to explore things similarity and relations from semantic Web perspective [Mietz et al. 2013; Christophe et al. 2011b] etc. In such cases, explicit relations of things can be characterized by using keyword-based textual-level calculations. However, physical things also hold *implicit* relations due to their more distinctive structures and connections in terms of their functionalities in real life (i.e., usefulness), as well as non-functionalities (i.e., availability). For example, different things provide different functionalities (e.g., microwave and printer), and will be of interest to different groups of people. With the development of ubiquitous computing, human-thing interactions can be easily recorded and obtained. These interactions are not completely random. They carry rich information that can be harnessed and utilized to uncover the implicit relations. Although correlations between things are *implicit*, we argue that they can be captured by exploring regularities of user interactions with similar things.

In this work, we consider a model for efficiently capturing and characterizing the contextual similarity of things by exploiting human-thing interactions. Such model can be applicable in a broad areas of the Internet of Things area, where a large amount of human-thing interactions can be recorded. For extracting contextual similarity of
things by analyzing such kind of data, first there is a way to obtain the contextual attributes attached on the human-thing interactions. Then, a model should be built that can effectively incorporate heterogeneous contextual information and a similarity measurement should be deployed for quantifying the things similarity on contextual level.

This work targets mining of useful information for unveiling implicit similarity of things from contextual information of human-thing interactions. Our proposed method, *DisCor-T* (discovering correlations of things), should be effective in capturing and reflecting the hidden structure of things from things usage events in the modeling stage, and efficient in inferring the related things in the inferring stage. Specifically, we present a novel approach that converts the things usage events into a relational graph of things (RGT) by extracting three dimensional contextual information contained in the events history. The RGT graph underpins many important applications. We particularly present an application scenario to show its advantage in serving things clustering and annotation. To the best of our knowledge, no previous work has systematically studied mining the relationships of ubiquitous objects. The main contributions of our work can be summarized as follows:

— We study the problem of managing ubiquitous things, which have unique characteristics (e.g., short descriptions, diverse, dynamic and noisy). We propose to investigate human-thing interactions from three contextual aspects: user, temporal, and spatial. Accordingly, we develop two graph presentations that approximate corresponding relationships from user-thing interactions. These graphs lay the foundation for uncovering latent correlations among things.

— We develop an algorithm for discovering latent correlations among things by applying Random Walk with Restart over the two contextual graphs. The learned correlations are used to construct the relational graph of things (RGT), which can help in a number of important applications on things management. In particular, we focus on a systematic case study on things annotation.

— We establish a testing environment where things are tagged by RFID and sensors, and things usage events are collected in real-time. Using this real-world data with ~20,000 records collected from the testing environment over a period of four months, we conduct extensive experimental studies to demonstrate the feasibility of our proposed approach.

The remainder of the paper is organized as follows. In Section 2, we present some background information related to our work including motivating applications and and formal definitions of the research problems. We then introduce the details of our proposed methodology *DisCor-T* in Section 3. We further demonstrate the benefits of our approach by designing a feature-based things annotation method in Section 4. We report the implementation and experimental studies in Section 5. Finally, we review the related work in Section 6 and give some concluding remarks in Section 7.

2. BACKGROUND
In this section, we first describe several application scenarios underpinned by the techniques discussed in this paper. We then formally formulate the research problems target by our work.

2.1. Motivating Applications
Discovering underlying similarities except keyword-based similarity can allow for more meaningful and accurate things recommendation, classification and even contribute to context-aware activity recognition. We briefly discuss some of areas where things contextual similarity can be applicable.
Recommendation. Things recommendation is a crucial step for promoting and taking full advantage of the Internet of Things (IoT), where it benefits the individuals, businesses and society on a daily basis in terms of two main aspects. On the one hand, it can deliver relevant things to users based on users preferences and interests. On the other hand, it can also serve to optimize the time and cost of using IoT in a particular situation.

The underlying correlations of things can enhance the performance of generalized recommendation systems in the Internet of Things in terms of two main points: 1) due to the sparsity of thing-user interactions, widely used collaborative filtering recommendation systems fail to find similar users or things, since the methods of computing similarities assume that two users have invoked at least some things in common. Moreover, users who have never use any things can not be fed good results in the first place. 2) physical things have more distinctive structures and connections in terms of their functionalities in real life (i.e., usefulness), as well as non-functionalities (i.e., availability), which are saliently highlighted in contextual information of human-thing interactions.

Searching. Developing efficient searching approaches is a crucial challenge with rapid increase of vast amount of things connected to the Internet. Our approach adds one additional dimension to assist and reinforce current search techniques. For instance, semantic-based solutions require time-consuming preparation of prior knowledge such as defining the descriptions of things and their corresponding characteristics and concepts under a uniform format like Resource Description Framework (RDF). In addition, such solutions do not make full use of the rich information contained in users' historical interactions with things (e.g., implicit relations of different things). Our approach can effectively capture this information, which can be integrated with existing search solutions for better performance.

Context-aware Activity Recognition. Recognizing human activities from sensor readings has recently attracted much research interest in pervasive computing due to its potential in many applications, such as assisted living and healthcare. This task is particularly challenging because human activities are often performed in not only a simple (i.e., sequential), but also a complex (i.e., interleaved or concurrent) manner in real life.

Our proposed approach provides a new useful assistance means to infer human activities in a ubiquitous environment by taking advantages of reasoning with relationships of globally unique object instances. For example, dense sensing-based activity monitoring learns human activities by detecting and analyzing human-object interactions. By discovering correlations of objects, we can cluster and organize things into different structured groups based on their underlying relationships. In many cases, an activity could involve multiple relevant things including not only the things with similar functionality but also things with complementary functionality, which can be effectively uncovered by our proposed approach in this paper. For example, different things provide different functionalities (e.g., microwave and printer), and will be of interest to different groups of people. Pairwise things with strong correlations indicate either they have similar functionalities (i.e., microwave and roaster) or they have more likelihood to be used together. For instance, a water tap and a chop board are both in use when we prepare meals, since most of the time we need to wash cooking ingredients (e.g., vegetables) before chopping them.

2.2. Problem Statement and Definitions

The only data source used in our work is human-thing interactions, namely things usage events. Each event happens when a person interacts with a particular thing,
which carries three kinds of information: location, timestamp, and user. Each usage event record can be defined as a quadruplet ThingID, UserID, Timestamp, Location described as follows.

**Definition 1 (Things Use Log).** Each thing use log happens when a person interacts with a particular thing. Let \( O = \{o_1, ..., o_n\} \), \( U = \{u_1, ..., u_m\} \), \( Ts = \{ts_1, ..., ts_p\} \) and \( Loc = \{loc_1, ..., loc_q\} \) represent the set of things, users, timestamps and locations, respectively. A usage event of a thing \( o_i \), denoted by \( h \in H = \{h_1, ..., h_i\} \), \( h = <o_i, u, ts, loc> | o \in O \land u \in U \land ts \in Ts \land loc \in Loc \), indicates that user \( u \) has used a particular thing \( o_i \) located in a specific location \( loc \).

The problem targeted in this article can be therefore formulated as discovering the **latent correlations** among things by exploiting observable human-thing interactions with the goal of automatically distinguishing strong correlations of things from the weak ones. As illustrated in Figure 1 each ball denotes a thing in a three-dimensional space of identity, spatiality, and temporality. Things are discrete without distinctive explicit correlations (Figure 1 (a)). However, our proposed approach can derive latent connections among these things and form a relational graph of things, where their implicit relatedness can be revealed (Figure 1 (b)). Therefore, our goal can be formulated as follows in Problem 1.

**Problem 1 (Things Implicit Correlation Discovery).** Given a set of human-thing interactions of quadruplets (thing, user, timestamp and location), discovering the latent relations between things in a ubiquitous environment.

To complete this goal, there are two sequential subproblems we need to solve, which are defined as subproblem 1 and subproblem 2 respectively.

**Subproblem 1 (Modeling).** Given a collection of things usage events \( \mathcal{H} \), construct two graphical models \( G_m \) capturing relations between things and their spatial-temporal information, and \( G_u \) capturing relations between things and users.

**Subproblem 2 (Inferring).** Given constructed graphs induced from things usage events collection \( \mathcal{H} \), infer the similarities of counterparts for each thing.
3. PROPOSED METHODOLOGY

Our approach for correlation discovery of things involves two main stages corresponding to two subproblems defined in Section 2.2. The overall algorithm is shown in Algorithm 1. We firstly extract two types of graphs, namely the location-time-thing graph (Figure 2(a)) and the user-thing graph (Figure 2(b)). The graphs are deduced from thing usage events, which reflect object and its three related information in terms of spatio-temporal and social aspects. Then we perform random walk on these two graphs respectively to inference relationships of pairwise things, and sum them up as the overall pairwise correlations of things.

The first stage centers around building two graphs from things usage events. As illustrated in Figure 2, the spatio-temporal graph in Figure 2(a) captures the relations between things and their temporal and geographical influence, while the social graph in Figure 2(b) captures the social influence among users on interacting things. The technical details on how to construct these graphs will be described in Section 3.1 and Section 3.2 respectively. In the second stage, our goal is to derive the pairwise relevance scores for things. To achieve this, a random walk with restart (RWR) [Xia et al. 2009] is performed on the two constructed graphs. A relevance score is produced for any given node to any other node in the graph, presented as a converged probability. The value of the relevance score reflects the correlation strength between a pair of things. Based on the relevance scores, a top-k correlation graph of things can be constructed, upon which many advanced things management problems such as annotation and clustering can be solved by tapping the wealth of literature in graph algorithms. The technical details on this part can be found in Section 3.3.

3.1. Spatio-Temporal Graph Construction

A spatio-temporal graph such as the one shown in Figure 2(a) reflects the temporal pattern and spatial information hidden in the things usage events. In our approach, the spatial and temporal information of things usage events is treated as inseparable since they are mutually influential on detecting the correlations among things. Unlike virtual resources such as web pages, music or images, physical things such as restaurants and cookware usually provide more distinguished functionalists, and are...
Constructing social graph \( G \)

Constructing spatio-temporal graph \( G \)

%%% Stage 2: Inferencing correlations via traversing graphs

Obtaining transition probability matrix

In this paper, we argue that geographical influence rants are likely to be visited by people during lunch or dinner times. For the spatial movement via finding the periodical pattern between time and locations.

In a kitchen or similar locations (e.g., a dining room). We specifically explore the things are their physical locations and functioning times. For example, kitchenware are more frequently used during dining times and they have higher likelihood to stay.

***Stage 1: Graphs Construction (Section 3.1 and Section 3.2) %%%

Finding time periods for \( l_i \) and store as \( p_i \);

Constructing edges between \( l_i \) and \( p_i \);

Constructing spatio-temporal graph \( G_m \);

Constructing social graph \( G_f \).

Obtaining transition probability matrix \( P_m \) and \( P_f \) deduced from corresponding weight matrix \( W_m \) and \( W_f \) respectively;

Implementing Random Walk with Restart (RWR) over \( G_m \) and \( G_f \) to derive things correlation matrix \( R_m \) and \( R_f \) respectively;

Calculating weighted linear combination correlation matrix of things \( R = \alpha R_m + \beta R_f \).

ALGORITHM 1: DisCor-T

\[\text{Input:} \text{Sequences of things usage events } H \text{ (Definition [1]), User friendship matrix } F_u \]

\[\text{Output:} \text{Correlation matrix of things } R\]

%-%-% Stage 1: Graphs Construction (Section [3.1] and Section [3.2] %-%-%

/*Detecting periodical connection between time and location*/

A spatio-temporal graph has three sets of nodes, namely locations, things, and timestamps. It contains one type of intra-relation (i.e., representing similarities between locations) and three types of inter-relations between locations, things, and timestamps. Edges between times and things can be obtained from usage events, say, the weight of edge \( < loc, o > \in E_Y \) and \( < ts, o > \in E_Z \) is proportional to the number of times objects \( o \) is used in a location \( loc \) and at timestamp \( ts \). The inter-relation between location and time \( < loc, ts > \in E_X \), indicates the periodical patterns. Formally, we define the spatio-temporal graph \( G_m \) as the following:

DEFINITION 2 (SPATIO-TEMPORAL GRAPH). A spatio-temporal graph is denoted by \( G_m =< V_m, E_m > \). Here \( V_m = \text{Loc} \cup \text{Ts} \cup \text{O} \) where \( \text{Loc} \), \( \text{Ts} \) and \( \text{O} \) are the sets of locations, timestamps and things respectively. Edges \( E_m = E_{\text{Loc}} \cup E_X \cup E_Y \cup E_Z \) where \( E_{\text{Loc}} = \{ (loc, loc') : (loc, loc') \in \text{Loc} \times \text{Loc} \} \) and the weight of each edge \( E_{\text{Loc}}(i, i') \in E_{\text{Loc}} \) is associated with the similarity between location \( i \) and \( i' \). \( E_X = \{ (loc, ts) : (loc, ts) \in \text{Loc} \times \text{Ts} \} \) and the weight of each edge \( E_X(i, j) \in E_X \) is associated with a binary value, referring to whether location \( loc_i \) has periodic relationship with time interval \( ts_j \). \( E_Y = \{ (loc, o) : (loc, o) \in \text{Loc} \times \text{O} \} \) and the weight of each edge \( E_Y(i, j) \in E_Y \) is associated with the frequency that thing \( o_j \) in location \( loc_i \) is accessed. \( E_Z = \{ (ts, o) : (ts, o) \in \text{Ts} \times \text{O} \} \) and the weight of each edge \( E_Z(i, j) \in E_Z \) is associated with the frequency that thing \( o_j \) is accessed in time interval \( ts_i \).
A.8

The corresponding weight matrix $W_m$ of graph $G_m$ can be formulated as:

$$W_m = \begin{bmatrix} W_{\text{Loc}} & W_X & W_Y \\ W_X^T & W_{\text{Ts}} & W_Z \\ W_Y^T & W_Z^T & W_O \end{bmatrix}$$

(1)

where each of the entries in Equation (1) can be obtained as the following. $W_{\text{Loc}}$ indicates the similarity of each pair of locations. Given two locations, we measure their similarity using the Jaccard coefficient between the sets of things used at each location:

$$W_{\text{Loc}}(i, j) = \frac{|\Gamma^o_i \cap \Gamma^o_j|}{|\Gamma^o_i \cup \Gamma^o_j|}$$

(2)

where $\Gamma^o_i$ and $\Gamma^o_j$ denote the set of used things at location $i$ and location $j$ respectively. $W_{\text{Ts}}$ and $W_O$ should be 0 since we do not consider the relationships between timestamps and the ones between things. $W_Y$ and its transpose $W_Y^T$ are integers, indicating how often a thing is accessed in a location. Similarly, $W_Z$ and its transpose $W_Z^T$ are integers, which indicate how often a thing is accessed at a timestamp.

For defining relationship between time stamps and locations and their corresponding weight $W_X$ of graph $G_m$, we propose periodic patterns between locations and timestamps. Given a sequence of locations $\text{Loc} = \{\text{loc}_1, ..., \text{loc}_n\}$, our aim is to find their corresponding time period. To obtain relationship between time and location, we analyze the potential periods for each location and find the periodical pattern between locations and timestamps. A periodic pattern represents the repeat of certain usage event at a specific location with certain time interval(s).

Periodic patterns can be extracted by analyzing things usage events. In particular, we build a time series for each location where the elements of the time series are the number of time slots (e.g., 0 for the period of 0:00-1:00; 1 for 1:00-2:00 and so on) that a thing at a location is invoked. Given a sequence of locations, we adopt the Discrete Fourier Transform (DFT) method to detect the time periods in this discrete time-series sequence [Vlachos et al. 2004]. For each location, we define an integer sequence $S = \{s_1, s_2, ..., s_n\}$, where $s_i=1$ if the thing is used at this location at time $i$, and 0 otherwise. Essentially, this sequence can be transformed into a sequence of $n$ complex numbers $X(f)$ from the time domain to the frequency domain:

$$X(f_k/N) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} a(n) e^{-j2\pi kn/N}, k = 0, ..., N - 1$$

(3)

where $k/N$ denotes the frequency that each coefficient captures. As a result, DFT transforms the original sequences as a linear combination of the complex sinusoids $s_f(n) = e^{j2\pi fn/N}$. The Fourier coefficients represent the amplitude of each of these sinusoids after sequences $S$ is projected on them.

In order to accurately capture the general shape of a time-series using a spartan representation, one could reconstruct the signal using just its dominant frequencies (i.e., the ones that carry most of the signal energy). A popular way to identify the power content of each frequency is by calculating the power spectral density (PSD) of the sequence which indicates the signal power at each frequency in the spectrum. A well known estimator of the PSD is the periodogram. The periodogram $P$ is a vector
comprised of the squared magnitude of the Fourier coefficients $X(f_{k/N})$:

$$P(f_{k/N}) = ||X(f_{k/N})||^2, k = 0, 1, ..., \left\lfloor \frac{N-1}{2} \right\rfloor$$  \hspace{1cm} (4)

The $k$ dominant frequencies appear as peaks in the periodogram (and correspond to the coefficients with the highest magnitude). In order to specify which frequencies are important, we need to set a threshold and identify those frequencies higher than this threshold. Each element of the periodogram provides the power at frequency $k/N$ or, equivalently, at period $N/k$. That is, coefficient $X(f_{k/N})$ corresponds to periods $[\frac{N}{k}, ..., \frac{N}{k-1})$. Interested readers are referred to [Vlachos et al. 2004].

When obtaining the periodgram of each location, we can decide their corresponding peak points based on preset threshold. From the periodogram, we can find the location and its corresponding time range. One benefit of using the periodogram is that we can visually identify the peaks as the $k$ most dominant periods (period =1/frequency). For automatically returning the important periods for a set of location sequences, we can simply set a threshold in the power spectrum to distinguish the dominant periods. In Section 5.1, we describe how to extract location and time relationship from the usage events.

3.2. Social Graph Construction

For exploring the impact social links between users on things’ correlation discovery, we also construct a social graph, which is an augmented bipartite graph representing user interactions with things based on things usage events. As shown in Figure 2(b), such a graph contains two sets of entities, users $U$ and things $O$. There is one type of intra-relation between users (also called social connections) and one type of inter-relations: edges between users and things that can be obtained from usage events. Formally, the social graph is defined as the following:

DEFINITION 3 (SOCIAL GRAPH). A social graph, denoted by $G_f =< V_f, E_f >$, is an augmented undirected bipartite graph. Here $V_f = U \cup O$ where $U, O$ are the sets of users and things respectively. Edges $E_f = E_U \cup E_M$, where $E_U = \{(u, u') : (u, u') \in U \times U\}$ denotes the user social links (friendship) and each edge $E_U(i, i') \in E_M$ is associated with the similarity between user $u_i$ and user $u_{i'}$. $E_M = \{(u, o) : (u, o) \in U \times O\}$. In this graph, each edge between users and things $E_M(i, j) \in E_M$ is associated with the frequency that thing $o_j$ is accessed by user $u_i$.

The corresponding weight matrix $W_f$ of graph $G_f$ can be formulated as:

$$W_f = \begin{bmatrix} W_U & W_M \\ W_M^T & W_O \end{bmatrix}$$  \hspace{1cm} (5)

The entries in Equation 5 can be obtained as follows: $W_M$ and its transpose $W_M^T$ should be proportional to the number of times of a thing being used by the users. $W_O$ should be zero since we do not consider relationships between things. The weight $W_U$ of edges $E_M$ indicates the user similarity influenced by the social links between users, reflecting the homophily meaning that similar users may have similar interests. We use the cosine similarity to calculate $W_U$ as follows:

$$W_U(i, j) = \frac{e^{\alpha \cos(b(i), b(j))}}{\sum_{k \in \Omega(i)} e^{\alpha \cos(b(i), b(k))}}$$  \hspace{1cm} (6)
where \( \cos(b(i), b(j)) = \frac{b(i) \cdot b(j)}{\|b(i)\| \|b(j)\|} \), \( \Omega(i) \) is the set of the user \( i \)'s friends (i.e., \( j \in \Omega(i) \)), \( b(i) \) is the binary vector of things used by user \( i \), \( \| \cdot \| \) is the L-2 norm of vector \( b(\cdot) \), and \( \alpha \) is a parameter that reflects the preference for transitioning to a user who interacted with the same things.

3.3. Correlation Inference

After the two graphs \( G_m \) and \( G_f \) are constructed, we can perform the random walk with restart (RWR) [Xia et al. 2009] to derive the correlation between each pair of things. RWR provides a good relevance score between two nodes in a graph, and has been successfully used in many applications such as automatic image captioning, recommendation systems, and link prediction. The goal of using RWR in our work is to find other things that have top-k highest relevance scores for a given thing. The values of the relevance scores imply the strength of the correlations among things. In the following, we focus on using RWR on the spatio-temporal graph \( G_m \) for discovering correlations between things.

We assume the random walker starts from a thing node \( o_i \) on \( G_m \). The random walker iteratively transits to other nodes which have edges with \( o_i \), with the probability proportional to the edge weight between them. At each step, \( o_i \) also has a restart probability \( c \) to return to itself. We can obtain the steady-state probability of \( o_i \) visiting other vertex \( o_j \) when the RWR process is converged. The RWR process can be formulated as

\[
\pi_i = (1-c)P\pi_i + ce_i
\]

where \( \pi_i \in \mathbb{R}^{N \times 1} \), and weight matrix from graph \( G_m \) is \( W_m \in \mathbb{R}^{N \times N} \) (Section 3.1), \( e_i \in \mathbb{R}^{N \times 1} \) with \( i \)-th entry is 1, all other entries are 0. Equation \( 7 \) can be further formulated as:

\[
\pi_i = c(I-(1-c)P_m)^{-1}e_i = Qe_i
\]

where \( I \) is an identity matrix and \( P_m \in \mathbb{R}^{N \times N} \) is the transition matrix, which can be obtained based on weight matrix \( W_m \) of \( G_m \) by row normalization:

\[
P_m = W_mD_m^{-1}
\]

where \( D_m \) is a diagonal matrix with \( D_m(i,i) = \sum_j W_m(i,j) \). The random walker on thing \( o_i \) traverses randomly along its edges to the neighboring nodes based on the transition probability \( P_m(i,j), \forall j \in N(i) \), and the probability of taking a particular edge \( o_i, o_j \) is proportional to the edge weight over all the outgoing edges from \( o_i \) based on Equation \( 9 \).

In Equation \( 8 \), \( Q = c(I-(1-c)P_m)^{-1} = c\sum_{t=0}^{\infty}(1-c)^tP^t \) defines all the steady-state probabilities of random walk with restart. \( P^t \) is the \( t \)-th order transition matrix, whose elements \( p_{ij}^t \) can be interpreted as the total probability for a random walker that begins at node \( i \) and ends at node \( j \) after \( t \) iterations, considering all possible paths between \( i \) and \( j \). Since in our case we only consider relevance score between two things, if we vary the value of \( t \), we can explicitly explore relationship between two things at different scales. The steady-state probabilities for each pair of nodes can be obtained by recursively processing Random Walk and Restart until convergence. The converged probabilities give us the long-term visiting rates from any given node to any other node. This way, we can obtain the relevance scores of all pairs of thing nodes, denoted by \( R_m(o_i,o_j) \in \mathbb{R}_m, \forall o_i, o_j \in O \). It should be noted that the results can be calculated more efficiently by using the Fast Random Walk with Restart implementation [Tong et al. 2006] via low-rank approximation and graph partition.
Similarly, the transition probability matrix \( P_f \) for the social graph \( G_f \) can be obtained using:

\[
P_f = W_f D_f^{-1}
\]

where \( D_f \) is a diagonal matrix with \( D_f(i, i) = \sum_j W_f(i, j) \). Accordingly, we can obtain the relevance scores of things on this graph \( R_f(o_i, o_j) \) for any pair of things.

The overall relevance score (i.e., the correlation value) of any pair of things can be calculated using

\[
R(o_i, o_j) = \alpha R_m(o_i, o_j) + \beta R_f(o_i, o_j)
\]

where \( \alpha \in [0, 1] \) and \( \beta \in [0, 1] \), which are regulatory factors affecting the weight on the social influence and the spatio-temporal influence.

With obtained correlation values, we could construct a top-\( k \) correlation graph of things by connecting each thing with the things that have top-\( k \) overall correlation values \( R(o_i, o_j) \). Formally, the graph is defined as the following:

**Definition 4 (Relational Graph of Things (RGT)).** RGT is denoted by \( G = (O, E) \). For each thing \( o_i \in O \), let \( O^i_k \) denote the top-\( k \)-set of correlative things to \( o_i \), \( E = \{ e(x, i) | o_i \in T, o_x \in O^i_k \} \), where \( e(x, i) \) is an edge from \( o_x \) to \( o_i \). Each edge is associated with a weight \( w_{o_x, o_i} \) with the correlation value \( R(x, o_i) \).

### 4. Applicability of DisCor-T: Things Classification

The top-\( k \) correlation graph \( G \) is essentially a graph representing the relationships among things. Using the constructed \( G \), many problems centered around things management (e.g., things discovery, search and recommendation) can be solved and explored further by exploiting existing graph algorithms. In this section, we will showcase the feasibility and effectiveness of our proposed DisCor-T by detailing one important research problem, automatic things annotation, which will be used later to evaluate the performance of our proposed approach.

Automatically predicting appropriate tags (i.e., category labels) for unlabeled things can save manual labeling workload, and has important research significance. Although some things have been labeled with useful tags (e.g., cooking, office), which are crucial for assisting users in searching and exploring new things, as well as recommending them, some other things may not have any meaningful labels at all. Furthermore, a thing might be associated with multiple categories. For instance, a microwave oven can be categorized in Cooking and also Home Appliance.

The aim of things annotation is that when given a new thing, the classifier automatically decides whether this thing belongs to the category of the corresponding labels. The algorithm can be divided into two stages: i) extracting features from the top-\( k \) correlation graph \( G \) and things, and ii) performing multi-label classification of things. We extract three kinds of features \( F_L \), \( F_S \) and \( F_C \) from RGT in terms of label property, link structures and node attributes respectively.

**Extracting feature \( F_L \).** This feature represents the label probabilities for unknown things, which can be computed using generative Bayesian rules from \( G \), where each unknown thing \( o^* \) is to be assigned one or multiple labels \( l_k \in L = \{l_1, ..., l_k\} \). We propose to formulate our solution as posterior probability \( Pr(l_k|o^*) \). Once we know these probabilities, it is straightforward to assign \( o_i \) the label having the top-\( K \) largest probabilities.
A:12

\[
Pr(l_k|o^*) = \frac{Pr(o^*|l_k)Pr(l_k)}{\sum_{j=1}^K Pr(x|l_j)Pr(l_j)} \propto Pr(o^*|l_k)p(l_k) \tag{12}
\]

where the prior distribution probability \(Pr(l_k)\) can be easily calculated from the training dataset. Let \(o^{l_k} = o^{l_k}_1, \ldots, o^{l_k}_{M_k}\) be the training dataset, having \(M_k\) things with label \(k\). Then \(Pr(o^*|l_k)\) can be calculated using:

\[
Pr(o^*|l_k) = \frac{1}{Z} \sum_{m=1}^{M_k} Pr(o^*|l^o_{m},l_k)Pr(o^o_m|l_k) \tag{13}
\]

where \(Z\) is a normalizing constant and the conditional probability \(Pr(o^*|o^o_m, l_k)\) indicates the relevance score between testing thing \(o^*\) and things in the training dataset \(o^o_m\). \(Pr(o^*|o^o_m, l_k) \approx \pi_{o^*}\) denotes the steady state probability between \(o^*\) and \(o^o_m\), which can be obtained from Equation \(8\) in our RWR process. The distribution \(p(o^o_m|l_k)\) is set as a uniform distribution \(1/M_k\). The probability \(p(o^*|l_k)\) can be predicted in Equation \(13\) and the labels with different posterior probabilities can be assigned to the testing thing. As a result, we can get the label probabilities for each testing object.

**Extracting latent feature** \(F_s\). With RGT, we can easily extract the features of things from RGT indicating the things relationship with different communities on \(G\). In reality, things usually hold multiple relations. For instance, a thing might be shared among its owner, owner’s friends, co-workers, or family members. It might also be connected to other things based on functionality or non-functionality attributes. Detecting such relations from RGT, which can be used as a structural feature for things annotation, is naturally related to the task of modularity-based community detection [Leicht and Newman 2008]. Modularity is to evaluate the goodness of a partition of undirected graphs. The reason that we choose this method is that modularity has been shown to be an effective quantity to measure community structure in many complex networks [Tang and Liu 2009].

Modularity \(Q\) is like a statistical test that the null model is a uniform random graph model, where one vertex connects to others with uniform probability. It is a measure of how far the interaction deviates from a uniform random graph with the same degree distribution. Modularity is defined as:

\[
Q = \frac{1}{2m} \sum_{ij} \left( A_{ij} - \frac{d_i d_j}{2m} \right) \delta(s_i, s_j) \tag{14}
\]

Where \(A_{ij}\) is the adjacent matrix on the graph RGT, \(m\) is the number of edges of the matrix, \(d_i\) and \(d_j\) denote the degree of vertex \(i\) and out-degree of vertex \(j\), and \(\delta(s_i, s_j)\) are the Kronecker delta function that takes the value 1 if node \(i\) and \(j\) belong to the same community, 0 otherwise. A larger modularity \(Q\) indicates denser within-group interaction. So that, the modularity-based algorithm aims to find a community structure such that \(Q\) is maximized. In [Newman 2006], Newman proposes an efficient solution by reformulating \(Q\) as:

ACM Journal Name, Vol. V, No. N, Article A, Publication date: January YYYY.
\[ Q = \frac{1}{2m} S^T B S \]  
(15)

where \( S \) is the binary matrix indicating which community each node belongs to. \( B \) is the modularity function, is defined as the following:

\[ B_{ij} = A_{ij} - \frac{d_i d_j}{2m} \]  
(16)

Since our relational graph of things (RGT) is a weighted and directed graph, we need to make some modifications on \( Q \) to solve the equation. This involves two steps.

In the first step, we extend \( B \) to directed graphs. Based on [Leicht and Newman 2008], we rewrite the modularity matrix \( B \) as the following:

\[ B'_{ij} = A_{ij} - \frac{d_{in} d_{out}}{2m} \]  
(17)

where \( d_{in} \) and \( d_{out} \) are the in-degrees and out-degrees of all the nodes on the RGT graph.

In the second step, we extend \( B' \) to weighted graphs. To do so, we conduct further modification based on Equation 17. It can be rewritten further as below:

\[ B''_{ij} = W_{ij} - \frac{w_{in} w_{out}}{2m} \]  
(18)

where \( W_{ij} \) is the sum of weights of all edges in the RGT graph replacing the adjacency matrix \( A \). \( w_{in} \) and \( w_{out} \) are the sum of the weights of incoming edges adjacent to vertex \( t_i \) and the outgoing edges adjacent to vertex \( t_j \) on the RGT graph respectively. After these two steps, it should be noted that different from undirected situation, \( B'' \) is not symmetric. To use the spectral optimization method proposed by Newman in [Newman 2006], we restore symmetry by adding \( B'' \) to its own transpose [Leicht and Newman 2008], thereby the new \( Q_{new} \) is:

\[ Q_{new} = \frac{1}{4m} S^T (B'' + B''^T) S \]  
(19)

We then is able to calculate all the eigenvectors corresponding to the top-\( k \) positive eigenvalue of \( B'' + B''^T \) and assign communities based on the elements of the eigenvector [Newman and Girvan 2004]. We take the obtained modularity vectors as the latent features, which indicate things relationship to communities (i.e., a larger value means a closer relationship with a community).

**Extracting feature \( F_C \).** It is the set of content-based features extracted from thing descriptions. We convert the keywords vectors into tf-idf format, which assigns each term \( x \) a weight in a thing’s description \( d \), \( tf - idf(x, d) = tf(x, d) \times idf(x) \), where \( tf(x, d) \) is the number of times word \( x \) occurs in the corresponding thing’s description \( d \), and \( idf \) is the inverse text frequency which is defined as : \( idf(x) = \log \frac{|N|}{df(x)} \), where \( |N| \) is the number of texts in our dataset, and \( df(x) \) is the number of texts where the word \( x \) occurs at least once.

Based on our experience in ontology bootstrapping for Web services [Segev and Sheng 2012], we exploit Term Frequency/Inverse Document Frequency (TF/IDF)—a common method in IR for generating a robust set of representative keywords from a corpus of documents—to analyze things’ descriptions. It should be noted that the common implementation of TF/IDF gives equal weights to the term frequency and inverse
document frequency (i.e., \( w = tf \times idf \)). We choose to give higher weight to the idf value (i.e., \( w = tf \times idf^2 \)). The reason behind this modification is to normalize the inherent bias of the tf measure in short documents.

Finally, the set of feature vectors for the \( N \) things in the dataset \( \vec{v} = [\vec{v}_1, ..., \vec{v}_N] \) where \( \vec{v}_i \in \mathbb{R}^m \) is the feature vector for each thing. For better performance, we perform a cosine normalization for tf-idf vectors: \( \hat{\vec{v}} = \frac{\vec{v}}{|\vec{v}|_2} \) [Salton and Buckley 1988].

**Building a discriminative classifier.** After obtaining the features based on attributes of \( G \) and things, we combine the features (\( F_L + F_S + F_C \)) together and feed them into a discriminative classifier.

Our method is a very flexible feature-based method, where the structural features can be put into any discriminative classifier for classification. In this paper, we evaluate our method on SVM and Logistic regression. Specifically, we adopt LibSVM [Chang and Lin 2011] for one-vs-rest classification.

### 5. EVALUATION

In this section, we firstly describe our experimental settings, and then showcase the applicability and performance of our proposed technology based on feature-based things annotation. We also report the experimental results.

#### 5.1. Data Acquisition

We set up a testbed that consists of several different places (e.g., bedroom, bathroom, garage, kitchen etc), where approximate 127 physical things (e.g., couch, laptop, microwave, fridge etc.) are monitored by attaching RFID and sensors. Table I presents the statistics of things used in this paper. This task greatly benefits from our extensive experience in a large RFID research project [Wu et al. 2012; Wu et al. 2013]. Figure 3 shows a research prototype we developed that provides an environment where users can check and control things real time via a Web interface. Figure 4 (a) shows some RFID devices and sensors used in the implementation and Figure 4 (b) shows part of the kitchen setting in our testbed. In our implementation, things are exposed on the Web using RESTful Web services, which can be discovered and accessed from a Web-based interface. Figure 5 shows the architecture of our testbed.

| No. | Category                  | # Things | # Labels |
|-----|----------------------------|----------|----------|
| 1   | Entertainment              | 28       | 118      |
| 2   | Office                     | 20       | 51       |
| 3   | Cooking                    | 25       | 103      |
| 4   | Transportation             | 11       | 24       |
| 5   | Medicine/Medical           | 10       | 18       |
| 6   | Home Appliances            | 33       | 83       |

To collect the records of things usage events, we need to figure out i) how to detect a usage event when it is happening; and ii) how to retrieve this thing’s corresponding three contextual information.

There are two ways to detect usage events of things with two identification technologies used, namely sensor-based state changes and RFID-based mobility detection.

1 https://www.youtube.com/watch?v=t4DHt0vUulY
Sensor-based state changes. The usage of a thing instrumented with sensors is reflected by the changes of the thing's status. When the status is changed, the corresponding thing is used. For example, when the status of a microwave oven is turned from idle to working, we see that this oven is being used. For such event detections, we adopt sensors to track the state changes of things.

RFID-based mobility detection. We determine whether the RFID-enabled things are in use via detecting their mobility. The movement of a thing indicates that the thing is being used. For example, if a coffee mug is moving, it is likely that the mug is being used. For such detections, we adopt a generic method based on comparing descriptive statistics of the Received Signal Strength Indication (RSSI) values from RFID readers in consecutive sliding windows [Parlak et al. 2011]. The statistics obtained from two consecutive windows are expected to differ significantly when a thing is mobile. A threshold can be set to determine whether this difference is related to a mobility and can be regarded as a valid usage event.

Each usage event is associated with identity (user), temporal (timestamp) and spatial (location) information. To obtain the user information, in our current work, we use
a manual labeling method where each participant needs to mark and record their activities. For the temporal information, we choose to divide the time of one day into 24 equal intervals. Each interval is one hour. If the timestamps of a usage event collected is 9:07am, it will be assigned into the temporal cluster between 9:00am to 10:00am. It should be noted that other equal intervals (e.g., half hour for an interval) are also applicable to our approach.

To get the localization information, which indicates where is the things when it is used. In the localization step, our aim is to identify the coarse-grain locations, the zone where the object lies. We need to consider two situations for things, static and mobile. For static things (e.g., refrigerator, microwave oven), the location information of such things is prior knowledge. For mobile things (e.g., RFID-tagged coffee mug), we provide coarse-grain or fine-grain location information. For the coarse-grain method, since the Received Signal Strength Indication (RSSI) signal received from a tagged thing reveals its proximity to an RFID reader antenna. We divide an area into multiple zones and each zone is covered with a mutually exclusive set of RFID antennas. The zone scanned by the antenna with the maximum RSSI is taken to be the thing’s location. For the fine-grain method, it is determined by comparing the signal descriptors from a thing at unknown location to a previously constructed radio map or fingerprints. We use the Weighted $k$ Nearest Neighbors algorithm (w-kNN), where we find the most similar fingerprints and compute a weighted average of their 2D positions to estimate the unknown tag location [Ni et al. 2004].

To conduct experimental studies, we manually labeled 127 things with 397 different labels. It should be noted that some things belong to multiple categories, therefore having multiple labels. For example, a Wii device belongs to category label Entertainment as well as Home Appliance. This dataset serves as the ground-truth dataset in our experiments for performance evaluation. Ten volunteers participated in the data collection phase by interacting with RFID tagged things for a period of four months, generating 20,179 records on the interactions of the things tagged in the experiments.
5.2. Metrics
We use micro-F1 and macro-F1 as evaluation measures. The F1 measure is the harmonic mean of Precision \((P)\) and Recall \((R)\), which can be calculated as: 
\[
F_1 = \frac{2 \times P \times R}{P + R}
\]

The Micro-F1 is defined as:
\[
Micro - F1 = \frac{2 \sum_{j=1}^{c} \sum_{i=1}^{n} \hat{y}_{c}^{i} y_{c}^{i}}{\sum_{j=1}^{c} \sum_{i=1}^{n} \hat{y}_{c}^{i} + \sum_{j=1}^{c} \sum_{i=1}^{n} y_{c}^{i}}
\]  \(20\)

where \(n\) is the number of testing data, \(c\) denotes the category label, \(y_{c}^{i}\) is the true label vector of the \(i\)-th sample, \(\hat{y}_{c}^{i} = 1\) if the instance belongs to category \(j\),  \(-1\) otherwise, \(\hat{y}_{c}^{i}\) is the predicted label vector. The micro-F1 measure weights equally on all samples, thus favoring the performance on common category labels. Macro-F1 is calculated as mean arithmetical value for F1 on each label. It measures weights equally on all the category labels regardless of how many samples belong to it, thus favoring the performance on rare category labels. Macro-F1 is defined as:
\[
Macro - F1 = \frac{2 \sum_{i=1}^{n} \hat{y}_{c}^{i} y_{c}^{i}}{n^2 |c| (\sum_{i=1}^{n} \hat{y}_{c}^{i} + \sum_{i=1}^{n} y_{c}^{i})}
\]  \(21\)

5.3. Experimental Results
In this section, we study the performance of our proposed DisCor-T approach based on things annotation described in Section 4. In particular, we will report the evaluation results for things annotations in terms of i) sensitivity analysis on varying weight value \(\alpha\) and \(\beta\) in Equation 11; ii) overall performance with different configurations of features, and iii) impact on introducing spatio-temporal integrity in our approach.

5.3.1. Parameters Tuning. This experiment aims at studying the impact of tuning parameters \(\alpha\) and \(\beta\) in Equation 11 on different categories of things. We varied the \(\alpha\) from 0.1 to 0.9 increment with 0.1 each time, while \(\beta\) was varied from 0.9 to 0.1 decrement with 0.1 each time, and implemented our annotation algorithm on the produced graph to evaluate the annotation performance. The results on the six categories of things are shown in Figure 6.

We can see some interesting patterns from the figures. For instance, with bigger temporal-spatial weight \(\alpha\) and smaller social weight \(\beta\), the annotation algorithm has better performance on Cooking and Home Appliance categories. It means both of these categories are sensitive to the temporal-spatial information but not the user aspect, i.e., the impact of \(\beta\) on classification of these categories is very limited. The possible reason is that things in these categories are connected by tight contextual relevance for their regular users. As a result, there presents little improvement when increasing the weight of the user aspect. On the contrary, we observe that for categories Entertainment and Transportation, the user aspect shows obvious impact since better performance is obtained when \(\beta\) increases. The possible reason is that these categories show some obvious convergence for common users. For the categories of Office and Medicine/Medical, they do not possess obvious preference over social or contextual (temporal-spatial) information. For example, it is hard to find a common time for people to receive initial treatment of injuries or illnesses at work place, which usually happen randomly.

5.3.2. Overall Performance. This experiment evaluates the performance of things annotation described in Section 3.3. We randomly removed the category tags of a certain percentage, ranging from 10% to 50%, of things from each category of the ground-truth
Fig. 6. Parameters tuning measured by MicroF1 and MacroF1 with different $\alpha$ and $\beta$ on six categories.

| Category          | $\alpha$ | $\beta$ |
|-------------------|----------|---------|
| Entertainment     | 0.4      | 0.6     |
| Office            | 0.5      | 0.5     |
| Cooking           | 0.8      | 0.2     |
| Transportation    | 0.4      | 0.6     |
| Medicine/Medical  | 0.5      | 0.5     |
| House Appliances  | 0.9      | 0.1     |
dataset. These things were used to test our approach while the rest were used as the training set. Our algorithm produces a vector of probabilities, representing the assignment probabilities of all labels for an unknown object. In our experiments, we ranked these probabilities and chose the top $k$ labels to compare with the ground truth labels. The $k$ value was set to the number of ground truth labels for each unknown object and it varies from object to object. The parameters $\alpha$ and $\beta$ were set as 0.5 each.

We particularly compared the annotation performance by using i) the features obtained from $G$, ii) the features obtained from thing descriptions (i.e., content features $F_C$), and iii) the combination of the both. Each process was repeated 10 times and the average results were recorded. Similar observations were obtained for different testing percentages. Figure 7 shows the result when we removed 30% of things from each category of the ground-truth dataset.

Descriptions of things are normally short and noisy, it is therefore not surprising that the performance based on content features only is worse than the one based on implicit structural features (i.e., $F_L + F_S$) in most categories. The consistent good performance from the latent features also indicates that our top-$k$ correlation graph $G$ is able to capture the correlations among things well. From the figure, we can see that by combining the two together, the performance of all six categories is increased and is the best consistently among the three.

5.3.3. Impact of Integrating Spatio-Temporal Information. As indicated in Section 3.1 user interactions with physical things usually present strong spatial-temporal correlations. In our approach, we treat spatial and temporal information of things usage events inseparable and believe that this integration would offer better performance in discovering correlations among things.
To validate this idea, we constructed two independent graphs based on time and location information from things usage events. Then random walk with restart (RWR) was performed in these two graphs separately. Together with the constructed social graph, a relational graph of things was constructed as described in Section 3.3. We label this approach as No-STI (without spatio-temporal integration) and our approach as STI. In this experiment, we focus on studying impact of set $\alpha = 1$ (i.e., $\beta = 0$) indicating that we only derive the $R$ based on our spatial-temporal graph (see Equation 11), and we also compare it with our previous work [Yao and Sheng 2012], where we constructed two independent graphs based on time and location information, and then sum them up to get the overall relevance. In this way, the spatio-temporal information are treated independently.

We performed things annotation by using features obtained from two different relational graphs of things and Table III shows the results when we removed 30% of things from each category of the ground-truth dataset. The table clearly shows that the annotation performance is enhanced for almost all categories by introducing spatio-temporal integrity and Medical/Medicine is the only exception. The reason is that user interactions with things in this category do not have strong connections with spatio-temporal patterns. In other words, people usually do not show periodic patterns when accessing medical related things (e.g., only when they are sick).

6. RELATED WORK

In this section, we review some existing research efforts that are closely related to our work.

6.1. Relational Learning

Relational learning refers to the classification in a context where things or entities present multiple relations [Tang and Liu 2009]. One main technique on relational learning is based on the Markov assumption, where the labels of a node in a relational network are determined by the labels of nodes in its neighborhood. Collective inference [Angelova and Weikum 2006; Jensen et al. 2004] and semi-supervised learning on graphs [Zhu et al. 2003] work on this assumption, which is constructed based on the relational features of labeled data, followed by an iterative process (e.g., relaxation labeling method) to determine class labels for unlabeled data. In [Ye et al. 2011], Ye et al. applied this methodology in location-based social networks for deriving label probabilities for places. The authors used the collective classification method that learns labels from the neighborhood, which only includes the nodes that hold the top-$k$ relevance with the prediction node. Collective inference and semi-supervised learning on graphs are limited in capturing local dependencies of nodes in the relational network.

Some improvement on semi-supervised learning algorithms focused on the dependency between labels [Liu et al. 2006], while some other work tried to capture the long-distance relevance of nodes. For example, [Miller et al. 2009] proposed a nonparametric latent feature models for link prediction. In [Neville and Jensen 2005], Neville and Jensen used clustering algorithm to find cluster membership and fix the latent group variables for inference. However, these approaches are not suitable for networks with a large number of things where computational costs for inference are prohibitive.

In our work, we extend the model to the relational network of things where a thing’s usage history not only indicates user and temporal information, but also location information. As a result, a better performance in deriving latent features from the relational network of things can be achieved. In particular, we explore the relation between spatial information and temporal information by exploring the periodical pattern in human interactions on things.
6.2. Ubiquitous Things Searching

Finding related and similar things is a key service and the most straightforward method of finding related things is the traditional keyword-based search, where user querying keyword is matched with the extracted description of things including textual descriptions on thing’s functionalities and non-functional properties. For example, in Microsearch [Tan et al. 2010] and Snoogle [Wang et al. 2008], each sensor is attached to a connected object, which carries a keyword-based description of each object. Following an ad hoc query consisting of a list of keywords, the system returns a ranked list of the top \( k \) entities matching this query. As we pointed out, this method can not work well for ubiquitous things due to unique characteristics, e.g., insufficient description of things, inconsistency of the meaning of the textual information, more importantly this solution does not make use of implicit inter-correlations between things and their rich contextual information.

Another mainstream solution is via semantic Web related techniques. Such solutions typically use the meta data annotation (e.g., details related to a sensor such as sensor type, manufacturer, capability and contextual information), then use a query language to search related available things [Mietz et al. 2013; Christophe et al. 2011b]. Online sensors such as Pachube, GSN [Aberer et al. 2006], Microsoft SensorMap [Nath et al. 2007] and linked sensor middleware [Le-Phuoc et al. 2011] support search for sensors based on textual metadata that describes the sensors (e.g., type and location of a sensor, functional and non-functional attributes, object to which the sensor is attached), which is manually entered by the person who deploys the sensor. Other users can then search for sensors with certain metadata by entering appropriate keywords. Unfortunately, these ontology and their use are rather complex and it is uncertain whether end users can provide correct descriptions of sensors and their deployment context without the help from experts. In other words, such methods require extensive prior knowledge. There are efforts to provide a standardized vocabulary to describe sensors and their properties such as SensorML and the Semantic Sensor Network Ontology (SSN) but not widely adopted.

The above solutions are time-consuming and require expert knowledge. For example, the descriptions of things and their corresponding characteristics and ontology need to be predefined under a uniform format such as Resource Description Framework (RDF) or Schema.org. In addition, the methods do not make full use of the rich information on users historical interactions with things, which may imply containing implicit relations of different entities. For example, if some users have the similar usage pattern on certain things, it may indicate some close connections among these things. Existing solutions can not capture such information well. We propose to extract the underlying connections between things by exploiting the human-thing interactions in ubiquitous environment. Our method not only takes rich contextual information of human-thing interactions into account, but also utilizes the historical pattern by analyzing past human-thing interactions.

7. CONCLUSION

Recent advances in radio-frequency identification (RFID), wireless sensor networks, and Web services have made it possible to bridge the physical and digital worlds together, where ubiquitous things are becoming an integral part of our daily lives. Despite the exciting potential of this prosperous era, there are many challenges that

2https://pachube.com/
3http://www.opengeospatial.org/standards/sensorml
4http://www.w3.org/2005/Incubator/ssn/ssnx/ssn
5http://schema.org/
persist. In this paper, we propose a novel model that derives latent correlations among things by exploiting user, temporal, and spatial information captured from things usage events. This correlation analysis can help solve many challenging issues in managing things such as things search, recommendation, annotation, classification and clustering. The experimental results demonstrate the utility of our approach. We view the work presented in this paper as a first step towards effective management of things in the ubiquitous computing era. There are a few interesting directions that we plan to work on to further improve our method.

— **Real-time things status update.** In real situation, physical things are more dynamic compared to traditional Web resources. Examples of such dynamic features include availability, and changing attributes (e.g., geographical information, status). We plan to improve our model so that it can adaptively propagate up-to-date information from things correlations network and make more accurate recommendations.

— **Scalability.** We plan to improve the scalability of our approach by adopting constrains in searching a local area. This can be realized by applying generalized clustering algorithms on hypergraphs. The search space can be significantly pruned this way. We also plan to evaluate the improved approach using large-scale datasets.

— **Thing-to-Thing communications.** Our current model works based on human-thing interactions to extract the latent connections between things. The communications between things are getting more prevalent with development of communication technologies, which represent a rich source to exploit for making our current model more robust. Extending our model by analyzing and exploring the thing-to-thing communications is another future work.

**REFERENCES**

Karl Aberer, Manfred Hauswirth, and Ali Salehi. 2006. A Middleware for Fast and Flexible Sensor Network Deployment. In Proc. of the 32nd Intl. Conference on Very Large Data Bases. 1199–1202.

Ralitsa Angelova and Gerhard Weikum. 2006. Graph-based Text Classification: Learn from Your Neighbors. In Proc. of the 29th Annual Intl. ACM SIGIR Conference on Research and Development in Information Retrieval. 485–492.

Chih-Chung Chang and Chih-Jen Lin. 2011. LIBSVM: a Library for Support Vector Machines. ACM Transactions on Intelligent Systems and Technology (TIST) 2, 3 (2011), 27.

Benoit Christophe, Vincent Verdot, and Vincent Toubiana. 2011a. Searching the Web of Things. In Proc. of ICSC. 308–315.

Benoit Christophe, Vincent Verdot, and Vincent Toubiana. 2011b. Searching the Web of Things. In Proceedings of the 5th International Conference on Semantic Computing (ICSC). IEEE, 308–315.

Alois Ferscha. 2012. 20 Years Past Weiser: What’s Next? IEEE Pervasive Computing 11, 1 (2012), 52–60.

Dominique Guinard, Vlad Trifa, Friedemann Mattern, and Erik Wilde. 2011. From the Internet of Things to the Web of Things: resource-oriented architecture and best practices. In Architecting the Internet of Things. Springer, 97–129.

D. Jensen, J. Neville, and B. Gallagher. 2004. Why Collective Inference Improves Relational Classification. In Proc. of the 10th ACM SIGKDD Intl. Conference on Knowledge Discovery and Data Mining. 593–598.

Tim Kindberg, John Barton, Jeff Morgan, Gene Becker, Debbie Caswell, Philippe Debaty, Gita Gopal, Marcos Frid, Venky Krishnan, Howard Morris, John Schettino, Bill Serra, and Mirjana Spasojevic. 2002. People, Places, Things: Web Presence for the Real World. Mobile Networks and Applications 7, 5 (2002), 365–376.

Danh Le-Phuoc, Hoan Nguyen Mau Quoc, Josiane Xavier Parreira, and Manfred Hauswirth. 2011. The Linked Sensor Middleware—Connecting the Real World and the Semantic Web. In Proceedings of the Semantic Web Challenge.

Elizabeth A Leicht and Mark EJ Newman. 2008. Community Structure in Directed Networks. Physical Review Letters 100, 11 (2008), 118703.

Yi Liu, Rong Jin, and Liu Yang. 2006. Semi-supervised Multi-label Learning by Constrained Non-negative Matrix Factorization. In Proceedings of the 21st National Conference on Artificial Intelligence (AAAI’06). 421–426.
Richard Mietz, Sven Groppe, Kay Römer, and Dennis Pfisterer. 2013. Semantic Models for Scalable Search in the Internet of Things. *Journal of Sensor and Actuator Networks* 2, 2 (2013), 172–195.

K.T. Miller, T.L. Griffiths, and M.I. Jordan. 2009. Nonparametric Latent Feature Models for Link Prediction. In *Proceedings of the 23rd Annual Conference on Neural Information Processing Systems (NIPS’09)*. 1276–1284.

Suman Nath, Jie Liu, and Feng Zhao. 2007. Sensormap for Wide-area Sensor Webs. *IEEE Computer* 40, 7 (2007), 90–93.

Jennifer Neville and David Jensen. 2005. Leveraging Relational Autocorrelation with Latent Group Models. In *Proceedings of the 4th International Workshop on Multi-relational Mining*. ACM, 49–55.

Mark E.J. Newman. 2006. Finding Community Structure in Networks Using the Eigenvectors of Matrices. *Physical review E* 74, 3 (2006), 036104.

Mark E.J. Newman and Michelle Girvan. 2004. Finding and Evaluating Community Structure in Networks. *Physical review E* 69, 2 (2004), 026113.

L.M. Ni, Y. Liu, Y.C. Lau, and A.P. Patil. 2004. LANDMARC: Indoor Location Sensing Using Active RFID. *Wireless Networks* 10, 6 (2004), 701–710.

Siddika Parlak, Ivan Marsic, and Randall S Burd. 2011. Activity Recognition for Emergency Care Using RFID. In *Proceedings of the 6th International Conference on Body Area Networks*. 40–46.

Gerard Salton and Christopher Buckley. 1988. Term-weighting Approaches in Automatic Text Retrieval. *Information Processing & Management* 24, 5 (1988), 513–523.

Aviv Segev and Quan Z. Sheng. 2012. Bootstrapping Ontologies for Web Services. *IEEE Transactions on Services Computing* 5, 1 (2012), 33–44.

Quan Z. Sheng, Sherali Zeadally, Zongwei Luo, Jen-Yao Chung, and Zakaria Maamar. 2010. Ubiquitous RFID: Where are we? *Information Systems Frontiers* 12, 5 (2010), 485–490.

Chiu C Tan, Bo Sheng, Haodong Wang, and Qun Li. 2010. Microsearch: A Search Engine for Embedded Devices used in Pervasive Computing. *ACM Transactions on Embedded Computing Systems (TECS)* 9, 4 (2010), 43.

Lei Tang and Huan Liu. 2009. Relational learning via latent social dimensions. In *Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM, 817–826.

Hanghang Tong, Christos Faloutsos, and Jia-Yu Pan. 2006. Fast Walk with Restart and Its Applications. In *Proceedings of the 6th International Conference on Data Mining (ICDM’06)*. Hong Kong, China.

Michail Vlachos, Christopher Meek, Zografoula Vagena, and Dimitrios Gunopulos. 2004. Identifying Similarities, Periodicities and Bursts for Online Search Queries. In *Proceedings of the 2004 ACM SIGMOD International Conference on Management of Data*. ACM, 131–142.

Haodong Wang, Chiu Chiang Tan, and Qun Li. 2008. Snoogle: A Search Engine for the Physical World. In *Proceedings of the 27th Conference on Computer Communications (INFOCOM 2008)*. IEEE.

Mark Weiser. 1991. The Computer for the 21st Century. *Scientific American* 265, 3 (1991), 94–104.

Yanbo Wu, Quan Z. Sheng, Damith Ranasinghe, and Lina Yao. 2012. PeerTrack: A Platform for Tracking and Tracing Objects in Large-scale Traceability Networks. In *Proceedings of the 15th International Conference on Extending Database Technology (EDBT)*.

Yanbo Wu, Quan Z. Sheng, Hong Shen, and Sherali Zeadally. 2013. Modeling Object Flows from Distributed and Federated RFID Data Streams for Efficient Tracking and Tracing. *IEEE Transactions on Parallel and Distributed Systems* 24, 10 (2013), 2036–2045.

Jing Xia, Doina Caragea, and William Hsu. 2009. Bi-relational Network Analysis Using a Fast Random Walk with Restart. In *Proceedings of the 9th IEEE International Conference on Data Mining (ICDM’09)*. IEEE, 1052–1057.

Lina Yao and Quan Z Sheng. 2012. Exploiting Latent Relevance for Relational Learning of Ubiquitous Things. In *Proceedings of the 21st ACM International Conference on Information and Knowledge Management (CIKM 2012)*. 1547–1551.

Lina Yao, Quan Z. Sheng, Byron Gao, Anne H.H Ngu, and Xue Li. 2013. A Model for Discovering Correlations of Ubiquitous Things. In *Proceedings of IEEE International Conference on Data Mining (ICDM 2013)*.

Lina Yao, Quan Z Sheng, Anne HH Ngu, Helen Ashman, and Xue Li. 2014. Exploring recommendations in internet of things. In *Proceedings of the 37th international ACM SIGIR conference on Research & development in information retrieval*. ACM, 855–858.

Mao Ye, Dong Shou, Wang-Chien Lee, Peifeng Yin, and Krzysztof Janowicz. 2011. On the Semantic Annotation of Places in Location-based Social Networks. In *Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM, 520–528.
Xiaojin Zhu, Zoubin Ghahramani, and John Lafferty. 2003. Semi-Supervised Learning using Gaussian Fields and Harmonic Functions. In Proc. of the 20th Intl. Conference on Machine Learning (ICML’03). 912–919.