Tensor-Based Link Prediction in Intermittently Connected Wireless Networks

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Abstract

Through several studies, it has been highlighted that mobility patterns in mobile networks are driven by human behaviors. This effect has been particularly observed in intermittently connected networks like DTN (Delay Tolerant Networks). Given that common social intentions generate similar human behavior, it is relevant to exploit this knowledge in the network protocols design, e.g. to identify the closeness degree between two nodes. In this paper, we propose a temporal link prediction technique for DTN which quantifies the behavior similarity between each pair of nodes and makes use of it to predict future links. Our prediction method keeps track of the spatio-temporal aspects of nodes behaviors organized as a third-order tensor that aims to record the evolution of the network topology. After collapsing the tensor information, we compute the degree of similarity for each pair of nodes using the Katz measure. This metric gives us an indication on the link occurrence between two nodes relying on their closeness. We show the efficiency of this method by applying it on three mobility traces: two real traces and one synthetic trace. Through several simulations, we demonstrate the effectiveness of the technique regarding another approach based on a similarity metric used in DTN. The validity of this method is proven when the computation of score is made in a distributed way (i.e. with local information). We attest that the tensor-based technique is effective for temporal link prediction applied to the intermittently connected networks. Furthermore, we think that this technique can go beyond the realm of DTN and we believe this can be further applied on every case of figure in which there is a need to derive the underlying social structure of a network of mobile users.

Keywords: Link prediction, wireless networks, intermittent connections, tensor, Katz measure, behavior similarity, DTN

1. Introduction

In recent years, extensive research has addressed challenges and problems raised in mobile, sparse and intermittently connected networks (i.e. DTN). In this case, forwarding packets tightly depends on contacts occurrence. Since the existence of links is crucial to deliver data from a source to a destination, the contacts and their properties emerge as a key issue in designing efficient communication protocols [1]. Obviously, the occurrence of links is led by the behavior of the nodes in the network [2]. It has been widely shown in [3, 4] that human mobility is directed by social intentions and reflects spatio-temporal regularity. A node can follow other nodes to a specific location (spatial level) and may bring out a behavior which may be regulated by a schedule (temporal level). The social intentions that govern the behavior of mobile users have also been observed through statistical analyses in [2, 3] by showing that the distribution of inter-contact times follow truncated power law.

With the intention of improving the performance of intermittently connected wireless network protocols, it is paramount to track and understand the behaviors of the nodes. We aim at proposing an approach that analyzes the network statistics, quantifies the social relationship between each pair of nodes and exploits this measure as a score which indicates if a link would occur in the immediate future. We strongly believe that the social ties between nodes highly govern the status of a link and establishes an indication for the link prediction: it would never occur if two nodes have no common social interactions and would rather be effective and lasting with more correlated moving patterns.

In this paper, we adapt a tensor-based link prediction algorithm successfully designed for the data-mining context [6, 7]. Our proposal records the network structure for T time periods and predicts links occurrences for the (T+1)th period. This link prediction technique is designed through two steps. First, tracking time-dependent network snapshots in adjacency matrices which form a tensor. Second, applying of the Katz measure [8] inspired from sociometry. The link prediction technique computes the degree of behavior similarity of each pair of nodes relying on the tensor obtained in the first step. A high degree of behavior similarity means that the two nodes have the
same “social” intentions. These common intentions are expressed by the willingness to meet each other and/or by similar moving patterns to visit a same location. They also promote the link occurrence between two socially close nodes in the immediate future (prediction of the period \(T+1\) after tracking the behaviors of nodes during \(T\) time periods).

We further discuss how we design the tensor-based prediction method and detail the two main steps in order to achieve link prediction. On the one hand, we describe how to track the network topology over time with a tensor. On the other hand, we explain how to compute and interpret the Katz measure. We then evaluate the effectiveness of predictability through several simulation scenarios depending on the nature of the trace (real or synthetic), the number of recording periods and the similarity metric computation which can be used in a centralized or distributed way. Besides, to the best of our knowledge, this work is the first to perform the prediction technique in a distributed way. The assessment of its efficiency can be beneficial for the improvement or the design of communication protocols in mobile, sparse and intermittently connected networks.

The paper is organized as follows: Section 2 presents the related work that highlights the growing interest to the social analysis and justifies the recourse to the tensors and to the Katz measure to perform predictions. In Section 3, we emphasize the two main steps that characterize our proposal. Section 4 details simulation scenarios used to evaluate the tensor-based prediction approach, analyzes the obtained results, assesses its efficiency and proposes a discussion about the described link prediction technique. Finally, we conclude the paper in Section 5.

2. Related Work

The Social Network Analysis (SNA) [9, 10] and ad-hoc networking have provided new perspectives for the design of network protocols [11, 12, 13]. These protocols aim to exploit the social aspects and relationship features between the nodes. Studies conducted in the field of SNA have mainly focused on two kinds of concepts: the most well-known centrality metrics suggested in [9, 11, 15, 16] and the community detection mechanisms proposed in [17, 18, 19, 9]. From this perspective, several works have tried to develop synthetic models that aim to reproduce realistic moving patterns [3, 20]. Nonetheless, the study done in [1] has outlined that synthetic models cannot faithfully reproduce the human behavior because these synthetic models are only location-driven and they do not track social intentions explicitly. We consider in this work the Time-Variant Community mobility model (TVC model) [3]. The TVC model depends on two main characteristics that influence the behavior of nodes: geographical location preferences and time-dependent behavior. This design tries to be closer to human-based behavior and implicitly reproduces the social aspects that characterizes ad-hoc networks.

Nevertheless, [10] has underlined the limits of these protocols when the network topology is time-varying. The main drawback comes down to their inability to model topology changes as they are based on graph theory tools. Nevertheless, the tensor-based approaches have been used in some works to build statistics on the behaviors of nodes in wireless networks over time as in [21]. Thakur et al. [4] have also developed a model using a collapsed tensor that tracks user’s location preferences (characterized by probabilities) with a considered time granularity (week days for example) in order to considered the emergence of “behavior-aware” delay tolerant networks.

In this paper, we propose a link prediction technique that tracks the temporal network topology evolution in a tensor and computes a metric in order to characterize the social-based behavior similarity of each pair of nodes. Some approaches have addressed the same problem in data-mining in order to perform link prediction. Acar et al. [6] and Dunlavy et al. [7] have provided detailed methods based on matrix and tensor factorizations for link prediction in social networks such as the DBLP data set [22]. These methods have been successfully applied to predict a collaboration between two authors relying on the data set of the structures of relationships over time. Moreover, they have highlighted the use of the Katz measure [8], which can be seen as a similarity metric, by assigning a link prediction score for each pair of nodes. The efficiency of the Katz measure in link prediction has been also demonstrated in [23, 24].

3. Description of the Tensor Based Prediction Method

It has been highlighted that a human mobility pattern shows a high degree of temporal and spatial regularity, and each individual is characterized by a time-dependent mobility pattern and a trend to return to preferred locations [2, 3, 4]. In order to improve the design of wireless network protocols, and especially the intermittently connected networks, it is important to exploit this knowledge since these interactions usually have an impact on the network structure and consequently on the network performance. Thus, in this paper, we propose an approach that aims to exploit similar behavior of nodes in order to predict link occurrence referring to the social closeness.

Predicting future links based on their social closeness is a challenge that is worth an investigation. Indeed, a good link prediction technique contributes to improve the opportunistic forwarding of packets and also enhances the delivery rate and/or decreases latency. Moreover, it helps to avoid situations where packets encumber the queue of the nodes that are not able to forward them towards their final destinations.

To quantify the social closeness between each pair of nodes in the network, we use the Katz measure [8] inspired from sociometry. This measure aims at measuring the social distance between persons inside a social network. We
also need to use a structure that records link occurrence between each pair of nodes over a certain period of time in order to perform the similarity measure computation. The records represent the network behavior statistics in time and space. To this end, tensors are used. A tensor \( Z \) consists in a set of slices and each slice corresponds to an adjacency matrix of the network tracked over a given period of time \( D \). After the tracking phase, we reduce the tensor into a matrix (or collapsed tensor) which expresses the weight of each link according to its lifetime and its recentness. A high weight value in this matrix denotes a link whose corresponding nodes share an important degree of closeness. We apply the Katz measure on the collapsed tensor to compute a matrix of scores \( S \) that not only considers direct links but also indirect links (multi-hop connections). The matrix of scores expresses the degree of similarity of each pair of nodes respecting to the spatial and the temporal levels. The higher the score is, the better the similarity pattern gets. Therefore, two nodes that have a high similarity score are most likely expected to have a common link in the future.

3.1. Notation

Scalars are denoted by lowercase letters, e.g., \( a \). Vectors are denoted by boldface lowercase letters, e.g., \( \mathbf{a} \). Matrices are denoted by boldface capital letters, e.g., \( \mathbf{T} \). Scalars are denoted by lowercase letters, e.g., \( a \). The \( r \)-th column of a matrix \( \mathbf{A} \) is denoted by \( \mathbf{a}_r \). Higher-order tensors are denoted by bold Euler script letters, e.g., \( \mathbf{X} \).

3.2. Matrix of Scores Computation

The computation of the similarity scores is modeled through two distinct steps. First, we store the intercontact between nodes in a tensor \( Z \) and reduce it to a matrix \( X \) called the collapsed tensor. In a second step, we compute the matrix of similarity scores \( S \) relying on the matrix \( X \) (cf. Fig. 1).

3.2.1. Collapsing the data from the tensor

We consider that the data is collected into the tensor \( Z \). The slice \( Z_t(i,j) \) describes the status of a link between a node \( i \) and a node \( j \) during a time period between \( [tD, (t+1)D] \) where \( Z_t(i,j) \) is 1 if the link exists during the time period \( D \) and 0 otherwise. The tensor is formed by a succession of adjacency matrices \( Z_1 \) to \( Z_T \) where the subscript letters designs the observed period. To collapse the data into one matrix as done in [6, 7], we choose to compute the collapsed weighted tensor (which is more efficient than collapsed tensor as shown in [6] and [7]). The links structure is considered over time and the more recent the adjacency matrix is, the more weighted the structure gets.

\[
X(i,j) = \sum_{t=0}^{T} (1-\theta)^{T-t} Z_t(i,j)
\]  

(1)

Where the matrix \( X \) is the collapsed weighted tensor of \( Z \), and \( \theta \) is a parameter used to adjust the weight of recentness and is between 0 and 1.

3.2.2. Katz Measure

The Katz measure, which is affiliated to sociometry, was first proposed by Leo Katz in [8]. He considers a social network as a undirected graph \( G = (V,E) \) where each vertices \( V = \{v_1, v_2, ..., v_k\} \) is a finite set of node that represent a persons and each edge \( E = \{e_1, e_2, ..., e_k\} \) is a finite set of connection (or an endorsement) between two persons. We denote a subset \( P_t(v_i, v_j) = \{e_1, e_2, ..., e_k\} \subset E \) as a path of length \( \ell \) between node \( v_i \) and \( v_j \). The score that characterizes the couple \( (v_i, v_j) \) is defined by the weight of paths \( P_t(v_i, v_j) \) connecting person \( v_i \) to person \( v_j \), \( \forall v \in V \).

Katz defined his metric between two nodes as \( S(i,j) \) as depicted in Eq. (2). It is a function that decreases proportionally to the path length \( P_t(v_i, v_j) \). Katz did so in order to emphasize the fact that endorsements strength fade over a successive chains of recommendations. This measure can be seen as a generalization of followers (as in Twitter) or an indegree measure. It indicates the number of votes of a person as well as the identity of the voter (his vote is valuable compared to the number of votes he receives). This metric is widely used in studies which aim to predict links occurrence [3, 7, 24], especially in social networks as co-authorships communities as the DBLP [22] and arXiv [25] databases. Given that there are “social relationships” between nodes in networks with intermittent connections, it is challenging to exploit this measure and to apply it on collected data. Therefore, the Katz score of a link between a node \( i \) and a node \( j \) is given by [8]:

\[
S(i,j) = \sum_{\ell=1}^{+\infty} \beta^\ell P_t(v_i, v_j)
\]  

(2)

Where \( \beta \) is a user defined parameter strictly superior to zero and \( \beta^\ell \) is the weight of a \( \ell \) hops path length. It is clear that the longer the path is, the lower the weight gets. There is also another formulation to compute Katz scores by means of collapsed weighted tensor as detailed previously. Then, the score matrix \( S \) can be rewritten as:

\[
S = \sum_{\ell=1}^{+\infty} \beta^\ell \cdot X^\ell = (I - \beta \cdot X)^{-1} - I
\]  

(3)

Where \( I \) is the identity matrix and \( X \) is the obtained collapsed weighted tensor.

In Fig. 1 we provide an example that describes the two main steps of the link prediction technique. We consider a network of 4 nodes whose topology is dynamic over time. At each period \( t \) (from 0 to 3), each occurred link
is caught in the corresponding adjacency matrix. All adjacency matrices form the tensor. The latter structure is used to determine the collapsed weighted tensor by computing Eq. 1 (by setting $\theta$ to 0.2) for each pair of nodes. Then, the matrix of scores is computed by applying Eq. 3 ($\beta$ is set to 0.001) on the collapsed weighted tensor.

The measure goes beyond estimating a link weight between two nodes. Indeed, it takes into consideration all possible paths between two nodes and then quantifies the social relationship between them. As described previously, when two nodes are connected through short paths, the score characterizing this pair is high. Hence, the score can be treated as the node’s moving pattern similarity, in view of the fact that the nodes conserve their vicinity (short paths). When two nodes share high score, this means that their behaviors are similar and that they are geographically quite close. Therefore, a link occurrence between them is very likely.

3.3. Matrix of Scores Interpretation

The relationship between each pair of nodes is expressed by a score $S_{ij}$, this score reflects the degree of similarity between node $i$ and node $j$. As mentioned in the Katz measure analysis, shorter paths lead to higher scores. Thus, two nodes that share a high score are nodes that are connected through short paths during some period of time and therefore have similar behaviors (similar social intentions). The similarity here is related to common preferences in spatial and temporal space. Two nodes maintain their connectivity when they move in the same direction and at the same time. Therefore, these scores can be considered as indicators to a possible link existence in the future. Thus, the link prediction is done through measuring behavior similarity for each nodes pairs in the matrix $S$.

The computation of matrix $S$, as described before, is done in a centralized way. It means that the matrix $S$ is computed based on a full knowledge of the network topology over time. This may not be suitable with ad hoc wireless networks where no central entity is considered and could in addition be very costly. A distributed mechanism should then be examined. In a distributed mechanism, each node would apply the prediction method relying only on information related to its nearest neighbors. It is paramount to remember that a Katz formulation gives more weight to short paths and assigns low scores to long paths. Therefore, the scores with neighbors located at few hops away should be sufficient and strong enough compared to scores with further ones. This hypothesis will be discussed in Section 3.

4. Performance Evaluation and Simulation Results

To evaluate how efficient is the tensor-based link prediction in intermittently connected wireless networks, we consider three different traces (two real traces and one synthetic trace). For each scenario, we compute the corresponding scores matrix $S$ as described earlier and assess the efficiency of the link prediction method through evaluation techniques. In the following, we firstly present the
traces used for the link prediction evaluation. Then, we expose the corresponding results and analyze the effectiveness of the prediction method.

4.1. Simulation Traces

We consider three traces to evaluate the link prediction approach. Two of them are real traces and the third is synthetic. We exploit them to construct the tensor by generating adjacency matrices (with different time period \(t\): 5, 10, 30 and 60 minutes). At each case, we track the required statistics about nodes behavior within \(T\) periods. We also consider the adjacency matrix corresponding to the period \(T+1\) as a benchmark to evaluate Katz scores matrix. We detail, in the following, the used traces.

- **First Trace: Dartmouth Campus trace**: We choose the trace of 01/05/06 [20] and construct the tensor slices relying on SYSLOG traces between 8 a.m. and midday (4 hours). The number of nodes is 1018.

- **Second Trace: MIT Campus trace**: We focus on the trace of 07/23/02 [27] and consider also the events between 8 a.m. and midday to build up the tensor. The number of nodes is 646.

- **Third Trace: TVC Model trace**: In this scenario, we use the trace generator proposed by Hsu et al. [28] which reproduces the concept of the TVC model. We consider a square simulation area with an edge length equal to 1000 meters and where 100 nodes are in motion. We randomly generate two locations as the node’s geographical preferences and keep community switching and roaming probabilities as in the example provided in the generator. As in the other scenarios, we track nodes behavior during 4 hours. Table 1 summarizes the main parameters considered in generating TVC Model traces.

| Parameter                              | Value    |
|----------------------------------------|----------|
| Simulation Area Edge Length            | 1000 meters |
| Network Nodes Number                   | 100 nodes |
| Network Nodes Range                    | 75 meters |
| Network Geographical Communities Number| 2        |
| Maximum Nodes Speed                    | 15 m/s   |
| Minimum Nodes Speed                    | 5 m/s    |
| Average Nodes Speed                    | 10 m/s   |

4.2. Performance Analysis

As described in the previous section, we apply the link prediction method to the three types of traces while considering the different tensor slice periods in both centralized and distributed cases. In order to assess the efficiency of this method, we consider several link prediction scenarios (according to the trace, the tensor slice period and the scores computation way) and we use different evaluation techniques (ROC curves, CDF curves, AUC metric and top scores ratio at \(T+1\)). We detail in the following the results obtained with each evaluation technique and analyze the link prediction efficiency.

4.2.1. Analysis of the ROC Curves

Fig. 2, 4 and 6 depict the ROC curves (Receiver Operating Characteristic) [29] for both distributed and centralized computing approaches respectively obtained from Dartmouth Campus trace, MIT Campus trace and TVC model trace. For each trace figure, (a), (b), (c) and (d) curves correspond to a tensor slice time of 5, 10, 30 and 60 minutes respectively.

We first notice that, for all scenarios, the prediction of all links is quite efficient, compared to the random guess (the curve’s bends are at the upper left corner). Moreover, two other observations have to be mentioned in the case of real traces (Dartmouth Campus and MIT Campus traces). First, it is highlighted that the smaller the tensor slice (adjacency matrix) period is, the more reliable the prediction gets. This observation is obvious for two reasons. On the one hand, with a low tensor slice time, the probability of tracking a short and occasional contact between two nodes is not likely. On the other hand, recording four hours of statistics requires 48 adjacency matrices of 5-minutes periods instead of 4 matrices for 60-minutes periods case. Thus, tracking a short contact between two nodes has less influence when the tensor slices are more numerous. As an example, in the case where the tensor slice time is 5 minutes, a fleeting contact can be caught by one adjacency matrix among 48. However, for the case where the slice time is 60 minutes, the fleeting contact is tracked by one tensor slice among 4, which significantly gives it more weight compared to the former case. Hence,
short tensor slice periods enable us to minimize the probability of tracking a short contact existence and to restrict its impact.

Short tensor slice periods also allow us to better track the social interactions (meetings in a cafeteria, courses in an amphitheater, etc) between nodes which determine the occurrence of links. Successive adjacency matrices of 5 minutes give more accurate description of network structure over time as both analyzing and identifying these social events are easier through smaller periods.

The second observation concerns the similar results obtained at the centralized and distributed matrix of scores computation. In fact, the similarity is higher when the paths considered between a pair of nodes are short. Thereby, paths that have more than two hops have weaker scores and so are less weighted compared to shorter ones. The distributed case assumes that each node knows its neighbors at most at two hops. That is why distributed scores computation presents performances which are so similar to the centralized ones.

Regarding the results obtained from the synthetic trace (TVC model trace), it is obvious that there are no significant differences between the ROC curves as the tensor slice periods vary (especially for the scenarios where the period $t$ is higher than 5 minutes). On top of having the same performances with the two scores matrix computation ways, changing the adjacency matrix time period does not impact the link prediction efficiency. This observation could be explained by the conclusion drawn by Hossmann et al. in [1] which outlines that location-driven mobility models do not care about social intentions. In addition, through the proposed behavior similarity metric between a pair of nodes, Thakur et al. in [4] prove that TVC model limits moving patterns to visiting preferred locations and do not take care of any social coordination. With TVC model, movement patterns are the same for all nodes (moving into two geographical communities) and repetitive (the chosen moving speed is between 5 and 15 m/s with an average speed of 10 m/s). They are only regulated by geographical preferences (each node visits the preferred community with an “individual willingness” and there is no correlation between its moving pattern and those of other nodes). Therefore, having several tensor slices is not different from considering fewer ones. Moreover, the adjacency matrix at $T+1$ in each scenario is quite the same.

### 4.2.2. Analysis of the CDF Curves

In order to highlight the impact of the choice of the period $t$ on the link prediction, we represent in Fig. 3 and 4 the skewed Cumulative Distribution Function (CDF) of the scores obtained respectively for Dartmouth Campus trace, MIT Campus trace and TVC model trace (only strictly positive scores are considered). At each trace’s CDF figure, (a) and (b) correspond to the distributed and centralized scores matrix computation respectively. The obtained results for real traces (Dartmouth Campus and MIT Campus) show that the spreading of distribution is narrower when the period $t$ is larger. In fact, at a CDF with wider spreading (especially at the case of $t=5$ min), high scores that express link occurrence prediction are easier to figure out. On the contrary, the interval of scores is narrow and so the score’s analysis is more imprecise. These results confirm the ones obtained through ROC curves. While the CDF results of real traces look similar, the ones of the synthetic trace show that the tensor slice period has a less significant impact. Indeed, the cumulative distribution functions are redundant at over 80% of obtained scores (when the scores are situated between 0 and $3.10^{-3}$). This observation also applies to ROC curves results.

As a final note, we underline that the synthetic trace CDF shows a higher percentage of weak scores than those of real traces. This observation explains the more limited prediction efficiency outlined with the TVC model trace.

### 4.2.3. Evaluation of the link prediction technique through performance metrics

As another evaluation step, adapted metrics are used in order to further weigh the performance of the proposed link prediction technique. At this step, on top of evaluating prediction of all links, we try to focus on assessing the efficiency of our technique in predicting new links that occurred for the first time at $T+1$ (while ignoring all previously seen links). To this end, we compute the Area Under the ROC Curve metric (AUC metric) [29] which could be considered as a good performance indicator in our case. Thus the top scores ratio metric at $T+1$ is also considered. To determine this metric, we compute the accurate number of links identified through the link prediction technique. We list, for each considered time period, the number of existing links at period $T+1$, which we call $L$. Then, we extract the links having the $L$ highest scores and determine the number of existing links in both sets. The evaluation metrics are computed for all traces with different tensor slice periods in both distributed and centralized scenarios. The results corresponding to all links prediction are listed in Table 2 (Dartmouth Campus trace), Table 3 (MIT Campus trace) and Table 4. The results corresponding to new links prediction are listed in Table 5, Table 6 and Table 7 respectively for Dartmouth Campus, MIT Campus and TVC model traces.

| Prediction Cases | Metrics | AUC | Top Scores Ratio at $T+1$ |
|------------------|---------|-----|--------------------------|
| Distributed Case and $t=5$ mins | 0.9850 | 2944/3267 (90.11%) |
| Centralized Case and $t=5$ mins | 0.9844 | 2945/3267 (90.14%) |
| Distributed Case and $t=10$ mins | 0.9917 | 2866/3240 (88.60%) |
| Centralized Case and $t=10$ mins | 0.9826 | 2866/3240 (88.60%) |
| Distributed Case and $t=30$ mins | 0.9369 | 2758/3832 (71.97%) |
| Centralized Case and $t=30$ mins | 0.9324 | 2758/3832 (71.97%) |
| Distributed Case and $t=60$ mins | 0.9153 | 2866/4270 (68.57%) |
| Centralized Case and $t=60$ mins | 0.9069 | 2926/4270 (68.52%) |
Regarding all links prediction results, we note, based on the high values of AUC metric (over than 0.9 at real traces) and top scores ratio obtained at $T+1$, that the prediction method is efficient in predicting future links. Moreover, we note that prediction is better when the tensor slice periods are shorter. We also observe that the centralized and distributed matrix of scores computation achieve similar performances. In addition, the results related to the top scores metric attests to the fact that the prediction of all links is efficient (at least 68% of links are identified and this percentage can exceed 90% in some cases) at both centralized and distributed scenarios. We also note that the previous observation regarding the redundancy of the results as the tensor slice period varies with the synthetic trace is confirmed. Indeed, The number of existing links at $T + 1$ is the same when the period $t$ is over 5 minutes. Moreover, AUC metric and top scores ratio has almost always the same value. Nonetheless, when the prediction only concerns new links, AUC metric values considerably decrease. This observation presumes that the prediction is not that accurate when only new links are considered. Given that new links are not tracked by the tensor, their scores are low (and even null). This interpretation is supported by the top scores ratio at $T + 1$. In fact, the percentages of identified new links are very low (no more than 8% in the best cases). Hence, the tensor-based link predic-
We depict in Fig. 8(a) and Fig. 8(b) the top scores ratio at $T + 1$ and the AUC, respectively, obtained for different values of $\theta$ and $\beta$. We can note that the values set to $\theta$ (i.e. 0.2) and to $\beta$ (i.e. 0.001) enables us to reach a quite efficient level of prediction. This results are relative to a prediction set performed on the MIT Campus trace with the distributed version of our method (as described in the Section 4.1).

4.2.4. Prediction Performance Comparison between the Tensor-Based Technique and the approach of Thakur et al.

We aim through this subsection to compare our proposal to another similar approach (we use the distributed approach to compute the scores). As we are designing a metric that expresses the degree of similarity of two nodes, we choose to compare the tensor-based technique performance to the one of the similarity metric suggested by Thakur et al. [4]. The latter metric measures the degree of similarity of the behaviors of two mobile nodes and the behavior of each node is expressed by an association matrix. The columns of the matrix represent the possi-

- (a) $5$ minutes tensor slice period
- (b) $10$ minutes tensor slice period
- (c) $30$ minutes tensor slice period
- (d) $60$ minutes tensor slice period

Figure 4: ROC Curves for different prediction cases applied on MIT Campus trace

- (a) Distributed computation of scores
- (b) Centralized computation of scores

Figure 5: Cumulative distribution function of Katz scores obtained from MIT Campus trace

It is also important underline the fact that our mechanism efficiency is dependent of chosen values of $\theta$ and $\beta$. We depict in Fig. 8(a) and Fig. 8(b) the top scores ratio at $T + 1$ and the AUC, respectively, obtained for different values of $\theta$ and $\beta$. We can note that the values set to $\theta$ (i.e. 0.2) and to $\beta$ (i.e. 0.001) enables us to reach a quite efficient level of prediction. This results are relative to a prediction set performed on the MIT Campus trace with the distributed version of our method (as described in the Section 4.1).
We compare the top scores ratio at $T+1$ and the area under the ROC curve metrics and we measure them for different tensor slice times or time granularities (5, 10, 30 and 60 minutes). For this comparison, we use the MIT trace of 07/23/02 and track adjacency matrices and/or association matrices from 8 a.m. to 3 p.m.. The associated results for the top scores ratio at $T+1$ and for the area under the ROC curve are respectively depicted in Fig. 9(a) and Fig. 9(b) and the performance gap are respectively displayed in Fig. 9(c) and Fig. 9(d).

We firstly focus on the comparison according to the top scores ratio at $T+1$. We underline that our proposal shows more efficient prediction ability compared to Thakur et al. framework especially when the tensor slice time/time granularity tends to be short. The different “natures” of the metrics used in each approach explain the results obtained for the two sets of comparison. Indeed, the measure quantifies the similarity of nodes based on their encounters and geographical closeness. In other words, the prediction measure cares about contacts (or closenesses) at (around) the same location and at the same time. Meanwhile, the

Figure 6: ROC Curves for different prediction cases applied on TVC model trace

Figure 7: Cumulative distribution function of Katz scores obtained from TVC model trace
similarity metric proposed by Thakur et al. is defined as an association metric. Hence, it measures the degree of similarity of behaviors of two mobile nodes without necessarily seeking if they are in the same location at the same time. As we have previously stated, the prediction performance of the tensor-based link prediction method is better with shorter tensor slice times. Then, with a longer tensor slice time, the interpretation of network statistics becomes less precise. This observation accounts for the prediction performance more comparable for both approaches with a larger tensor slice time/time granularity.

On the other hand the comparison based on the AUC metric, we remark that the two approaches show quasi-similar prediction efficiency with a slightly better performance for our proposal, mostly because the overwhelming number of non-effective links introduce a bias in the
calculations of the AUC metric. The reduced number of occurring links and the findings obtained for the first set of comparison explain the little AUC gap in favor of the tensor-based link prediction approach.

4.3. Discussion

In wireless networks and specifically in intermittently connected ones, it is important to exploit social relationships that influence nodes mobility. Taking advantage of the social aspect within these networks could ensure a better routing strategy and therefore improve the packets delivery rate and reduce latency. Through our proposal, we aim to track eventual similarities between mobility patterns of nodes and wisely exploit them for a better link prediction.

As seen earlier, link occurrence between two nodes is more likely when they have similar social behaviors. Then, identifying nodes that have similar mobility pattern could help to predict effective links between nodes in the future. The more accurate the link prediction is the more optimized the routing scheme could get. In fact, an efficient link prediction would help to make better decisions in the forwarding process. For example, a node would rather decide to postpone sending a packet to an eventual current next hop because the link prediction scheme estimates that a better forwarder (closer to the destination for example) is going to appear in the immediate future. Also, link prediction could prevent buffer overloading. Indeed, an overloaded node would rather drop a packet if the link prediction scheme indicates that there will not be any possible route toward the destination in the future and before the packet’s TTL expires. Through this approach, we can get quite efficient prediction results.

As mentioned previously, the efficiency of the technique used can exceed 90% of identified links (with slice period equal to 5 minutes). The link prediction relies on measuring the similarity of the mobility of nodes. Song et al. [31] have investigated the limits of predictability in human mobility. Relying on data collected from mobile phone carriers, they have found that 93% of user mobility is potentially predictable. The best predictability percentage reached by our approach agrees with the conclusion of Song et al..

We have also shown through the simulations that prediction efficiency is similar, for a specific scenario (type of trace and slice time period), in the case of both centralized and distributed computation of Katz scores. As we have explained, the distributed scheme is only able to
Table 8: Evaluation metrics for distributed prediction scenarios applied on MIT Campus trace

| Prediction Cases                | Metrics | AUC  | Top Scores Ratio at T=+1 |
|--------------------------------|---------|------|--------------------------|
| One-hop knowledge and t=5 mins |         | 0.9741 | 1921/2147 (89.47%)       |
| One-hop knowledge and t=10 mins|         | 0.9608 | 1922/2147 (89.52%)       |
| One-hop knowledge and t=30 mins|         | 0.9406 | 1757/2311 (76.02%)       |
| Two-hops knowledge and t=30 mins|       | 0.9631 | 1757/2311 (76.02%)       |

When the knowledge is limited to the neighbors at one hop, the closeness only means that it exists a direct link between two nodes. This scenario does not consider the relationships between nodes when they are separated by multi-hops paths. The results confirm that the prediction effectiveness is lesser. Even if the top scores ratios at T=+1 are close, the performance of the one-hop knowledge scenarios are slightly worse. The AUC metric attests also that the prediction is less efficient in such cases. In fact, considering the two-hops knowledge generates more significant true positive rate for the ROC curve (expressed by better top scores ratio at T=+1) while the false positive rate remains practically the same (due to the overwhelming number of noneffective links). Nevertheless, the best scenario to retain is not obvious to identify if we compare the cost of exchanging local information between nodes to the cost of less efficient link prediction. Future simulations and real deployments will enable us to determine which setting is preferable to consider.

5. Conclusion

Human mobility patterns are mostly driven by social intentions and correlations in the behaviors of people forming the network appear. These similarities quantifies the correlation between the spatial level in terms of visited locations and the temporal level regarding mobility correlation over period of time. The knowledge about the behavior of nodes greatly helps in improving the design of communication protocols. Intuitively, two nodes that follow the same social intentions over time promote the occurrence of link in the immediate future.

In this paper, we presented a link prediction technique inspired from data-mining and exploit it in the context of wireless networks. Our contribution in this paper, as a new link prediction technique for the intermittently connected wireless networks, is designed through two major steps. First, the network topology is tracked over several time periods in a tensor. Secondly, after collapsing the structural information, Katz measure is computed for each pair of nodes as a score. A high score means similar moving patterns inferring the closeness of the nodes and indicates that a link occurrence is likely in the future.

Through the link prediction evaluation, we have obtained relevant results that attest the efficiency of our contribution and agree with some findings referred in the literature. We summarize them in the following points:

- The tensor-based link prediction technique is quite efficient especially when applied on real traces (Dartmouth Campus and MIT Campus traces). The result are supported by the ROC curves and the evaluation metrics (AUC and Top Scores Ratio at T+1 metrics).
- Applied on real traces, the proposed prediction technique provides more accurate results with lower tensor slice (or tensor adjacency matrices) times.
- The prediction results with the synthetic trace (TVC model trace) confirm the lack of social interactions. The intentions of node are only governed by the preferred locations and do not correlate with the intentions of the other nodes.
- The link prediction method guarantees good performance when prediction is applied to all links. Nevertheless, the prediction of new links (not occurring according to statistics and by ignoring all links seen previously) is not accurate (very low AUC and top scores ratio at T+1 metrics).
• Applying the prediction technique in a distributed way (nodes knows only their neighbors at most at two hops) achieves similar predicting performance compared to the use in centralized way (an entity has full-knowledge about network structure over time).

• The temporal tensor-based link prediction described in this paper is based on an encounter metric which takes into account the occurring contacts at the same location and at the same time. We provide a performance comparison with a similar approach built around an association similarity metric (that quantifies similarity based on preferred locations regardless of time correlations) and show that our proposal achieves better prediction results.

Good link prediction offers the possibility to further improve opportunistic packet forwarding strategies by making better decisions in order to enhance the delivery rate or limiting latency. Therefore, it will be relevant to supply some routing protocols with prediction information and to assess the contribution of our approach in enhancing the performance of the network especially as we propose an efficient distributed version of the prediction method. The proposed technique also motivates us to inquire into future enhancements as a more precise tracking of the behavior of nodes and a more efficient similarity computation.

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References

[1] T. Hossmann, T. Spyropoulos, F. Legendre, Social network analysis of human mobility and implications for dtn performance analysis and mobility modeling, Tech. Rep. 323, Computer Engineering and Networks Laboratory ETH Zurich (July 2010).

[2] A. Chaintreau, P. Hui, J. Crowcroft, C. Diot, R. Gass, J. Scott, Impact of human mobility on opportunistic forwarding algorithms, IEEE Trans. on Mobile Computing 6 (6) (2007) 606–620.

[3] W.-J. Hsu, T. Spyropoulos, K. Psounis, A. Helmy, Modeling Spatial and Temporal Dependencies of User Mobility in Wireless Mobile Networks, IEEE/ACM Trans. on Networking 17 (5) (2009) 1564–1577.

[4] G. S. Thakur, A. Helmy, W.-J. Hsu, Similarity analysis and modeling in mobile societies: the missing link, in: Proc. of the 5th ACM workshop on Challenged networks (CHANTS ’10), 2010, pp. 13–20.

[5] T. Karagiannis, J.-Y. Le Boudec, M. Vojnovic, Power law and exponential decay of inter contact times between mobile devices, in: Proc. of the 13th annual ACM international conference on Mobile computing and networking, (MobiCom ’07), 2007, pp. 183–194.

[6] E. Acar, D. M. Dunlavy, T. G. Kolda, Link Prediction on Evolving Data Using Matrix and Tensor Factorizations, in: Proc. of the IEEE International Conference on Data Mining Workshops, 2009, pp. 262–269.

[7] D. M. Dunlavy, T. G. Kolda, E. Acar, Temporal link prediction using matrix and tensor factorizations, ACM Trans. Knowl. Discov. Data 5 (2) (2011) 10:1–10:27.

[8] L. Katz, A new status index derived from sociometric analysis, Psychometrika 18 (1) (1953) 39–43.

[9] S. Wasserman, K. Faust, Social Network Analysis: Methods and Applications, Cambridge University Press, 1994.

[10] D. Katsaros, N. Dimokas, L. Tassiulas, Social network analysis concepts in the design of wireless Ad Hoc network protocols, IEEE Network 24 (6) (2010) 23–29.

[11] P. Hui, J. Crowcroft, E. Yoneki, Bubble rap: social-based forwarding in delay tolerant networks, in: Proc. of the 9th ACM international symposium on Mobile ad hoc networking and computing (MobiHoc ’08), 2008, pp. 241–250.

[12] E. M. Daly, M. Haahr, Social network analysis for routing in distributed delay-tolerant MANETs, in: Proc. of the 8th ACM international symposium on Mobile ad hoc networking and computing, (MobiHoc ’07), 2007, pp. 32–40.

[13] T. Hossmann, T. Spyropoulos, F. Legendre, Know thy neighbor: Towards optimal mapping of contacts to social graphs for dtn routing, in: Proc. of IEEE INFOCOM, 2010, pp. 1–9.

[14] L. Page, S. Brin, R. Motwani, T. Winograd, The PageRank Citation Ranking: Bringing Order to the Web., Tech. rep., Stanford InfoLab, (1999).

[15] W. Hwang, T. Kim, M. Ramathanan, A. Zhang, Bridging centrality: Graph mining from element level to group level, in: Proc. of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining, 2008, pp. 336–344.

[16] F. R. K. Chung, Spectral Graph Theory (CBMS Regional Conference Series in Mathematics, No. 92), American Mathematical Society, 1997.

[17] B. Bollobas, Modern Graph Theory, Springer, 1998.

[18] M. E. J. Newman, Modularity and community structure in networks., Proceedings of the National Academy of Sciences of the United States of America 103 (23) (2006) 8577–82.

[19] G. Palla, I. Derényi, I. Farkas, T. Vicsek, Uncovering the overlapping community structure of complex networks in nature and society, Nature 435 (7043) (2005) 814–8.

[20] K. Lee, S. Hong, S. J. Kim, I. Rhee, S. Chong, Slaw: A new mobility model for human walks, in: Proc. of IEEE INFOCOM, 2009, pp. 855–863.

[21] U. G. Acer, P. Drineas, A. A. Abouzeid, Random walks in time-graphs, in: Proc. of the Second International Workshop on Mobile Opportunistic Networking, (MobiOpp ’10), 2010, pp. 93–100.

[22] The DBLP computer science bibliography, http://www.informatik.uni-trier.de/~ley/db/.

[23] C. Wang, V. Sataluri, S. Parthasarathy, Local Probabilistic Models for Link Prediction, in: Proc. of the Seventh IEEE International Conference on Data Mining, (ICDM ’07), 2007, pp. 322–331.

[24] D. Liben-Nowell, J. Kleinberg, The link-prediction problem for social networks, Journal of the American Society for Information Science and Technology 58 (7) (2007) 1019–1031.

[25] Cornell university library arxiv.org, http://arxiv.org/.

[26] CRAWDAD: A community resource for archiving wireless data at dartmouth, http://crawdad.cs.dartmouth.edu/.

[27] M. Balazinska, P. Castro, Characterizing mobility and network usage in a corporate wireless local-area network, in: Proc. of the 1st international conference on Mobile systems, applications, and services, (MobiSys ’03), 2003, pp. 303–316.

[28] Time-variant community mobility model, http://nile.cise.ufl.edu/~weijenh/TVC_model/.

[29] T. Fawcett, An introduction to ROC analysis, Pattern Recognition Letters 27 (8) (2006) 861–874.

[30] B. A. Horne, C. R. Johnson, Matrix Analysis, Cambridge University Press, 1990.

[31] C. Song, Z. Qu, N. Blumm, A.-L. Barabási, Limits of Predictability in Human Mobility, Science 327 (5968) (2010) 1018–1021.