Improving Link Prediction in Intermittently Connected Wireless Networks by Considering Link and Proximity Stabilities

Mohamed-Haykel Zayani, Vincent Gauthier and Djamal Zeghlache

Lab. CNRS SAMOVAR UMR 5157
Institut Mines-Telecom, Telecom SudParis
Evry, France

{mohamed-haykel.zayani, vincent.gauthier, djamal.zeghlache}@telecom-sudparis.eu

Abstract—Several works have outlined the fact that the mobility in intermittently connected wireless networks is strongly governed by human behaviors as they are basically human-centered. It has been shown that the users’ moves can be correlated and that the social ties shared by the users highly impact their mobility patterns and hence the network structure. Tracking these correlations and measuring the strength of social ties have led us to propose an efficient distributed tensor-based link prediction technique. In fact, we are convinced that the feedback provided by such a prediction mechanism can enhance communication protocols such as opportunistic routing protocols.

In this paper, we aim to bring out that measuring the stabilities of the link and the proximity at two hops can improve the efficiency of the proposed link prediction technique. To quantify these two parameters, we propose an entropy estimator in order to measure the two stability aspects over successive time periods. Then, we join these entropy estimations to the tensor-based link prediction framework by designing new prediction metrics. To assess the contribution of these entropy estimations in the enhancement of tensor-based link prediction efficiency, we perform prediction on two real traces. Our simulation results show that by exploiting the information corresponding to the link stability and/or to the proximity stability, the performance of the tensor-based link prediction technique is improved. Moreover, the results attest that our proposal’s ability to outperform other well-known prediction metrics.

Index Terms—wireless networks; intermittent connections; link prediction; tensor; Katz measure; link and proximity stabilities; entropy.

I. INTRODUCTION

Disruption Tolerant Networks (DTN) paradigm is an emerging wireless networking application where we have to deal with sparse and intermittent connectivity. In order to achieve a reasonable packet delivery rate, we have to rely on opportunistic or mobility-assisted routing, where messages are forwarded only when two nodes are in contact. Consequently, the packet delivery rate at the destination is strongly tied to the network structure during the forwarding process. Basically, as these networks are human-centered, the mobility patterns are governed by human behavior. Such a behavior highly impacts on the structure of the network as shown in [1], [2]. Moreover, it has been demonstrated in [3], [4], [5] that the human mobility is directed by social intentions that the network users share at the spatial and temporal levels. When the intentions of some people are correlated (to be present in the same locations at the same time), this favors their meeting and thereby the occurrence of links between them. In this way, mathematical models have been proposed to characterize the inter-contact time between two people through statistical analysis [1], [6]. Thus, it is crucial to better understand how links are created and to track their properties in order to design efficient communication protocols.

To analyze the network topology evolution, it is important to rely on records that describe the status of each link over time during a tracking period [7]. Extracting information about correlations between the willingness of people carrying the nodes is an important support which provides insights for predicting links. From this perspective, we have proposed in [8] a tensor-based link prediction technique. Our approach is based on a spatio-temporal framework that tracks the contacts between nodes. Hence, tracking the occurrence of links over successive time periods has enabled us to detect the degree of spatial closeness between the network users and then quantify their behavior similarity. Afterwards, this parameter has been used as an indicator to predict the occurrence of links in the immediate future.

In this paper, we aim to improve the performance of the tensor-based link prediction technique by refining the measure of behavior similarity. As we are convinced that link prediction enhances the performance of communication protocols, we want the feedback provided by our framework to be the most reliable possible. We find that the link and the proximity (at two hops) stabilities can also be considered as parameters to predict future links. Indeed, when some network users are related by strong social ties, the link between them tends to be persistent. In other words, when two network users have high correlated behaviors, their closeness is expected to lengthen and to remain stable. When nodes have information about their neighbors at two hops, the stability of such proximity, joined to the tensor-based link prediction method, also leads to the performance of more efficient link prediction. We detail how proximity stability can be beneficial later. Besides, measuring such stability measures is a key parameter which is
interesting to exploit. To quantify them, we propose a metric inspired by the Lempel-Ziv estimator [9] which converges to the entropy of a time series. To enhance the prediction performance of the tensor-based link prediction framework, we join the stability measures with its outputs by designing new prediction measures that identify future links as the ones which are relative to users that have strong (behavior similarity) and stable (proximity stability) closeness. Afterwards, we assess if our proposal really contributes to improve the prediction performance of the tensor-based link prediction method.

The paper is organized as follows: Section II briefly presents the related work. In Section III, we give an overview of the tensor-based link prediction technique. Section IV introduces the measure of the link and the proximity stabilities, presents the estimator used to approximate them and details some combinations of the stability measures with our link prediction technique in order to provide new prediction metrics. In section V, we present the simulation scenarios used to evaluate the contribution of these stability measures, define how to evaluate them and we analyze the obtained results. Finally, we conclude the paper in Section VI.

II. RELATED WORK

Due to the opportunistic aspect of forwarding in intermittently connected wireless networks and as these networks are basically human-centered networks, Social Network Analysis (SNA) [10] has been used in order to provide more efficient communication protocols. It has been applied to track and understand the relationships between the network entities and to extract structural information about the network (network robustness, topology variance, emerging communities, ...). Several communication protocols such as [11], [12], [13] have been based on SNA: they have used the centrality metrics proposed in [10], [14], [15], [16] and/or have exploited community detection mechanisms such as [10], [17], [18], [19]. These two categories of “social tools” have been defined as the two major concepts of SNA in the design of wireless ad-hoc network protocols by Katsaros et al. [20].

Tracking the social ties between the network entities has led to the design of techniques for link prediction. The link prediction in social networks has been addressed in the data-mining context [21], [22], [23], [24] and recently for the community-based communication networks [8], [25]. These works have highlighted salient measures that make possible to predict wireless links between network users. These measures determine if an occurrence of a link is likely by quantifying the degree of proximity of two nodes (Katz measure [26], the number of common neighbors, the Adamic-Adar measure [27], the Jaccard’s coefficient [28], [29], ...) or by computing the similarity of their mobility patterns (through such metrics as the spatial cosine similarity, the co-location rate, ...). The efficiency of the Katz measure has been especially emphasized compared to other prediction metrics in [22], [25]. Thanks to the SNA, it has been highlighted that the relationships between individuals has a major impact on the structure of the network [11], [2].

For the human-centered wireless networks, the social closeness between some people influences their mobility patterns. In [30], Song et al. have demonstrated that human mobility is potentially predictable in 93% of cases by using the traces of mobile users of a cellular phone network. This limit has been investigated through an estimation of the entropy proposed by Ziv and Lempel [9]. The entropy estimation has been applied on the sequence of visited locations for each mobile phone user during a tracking period. Song et al. have been motivated by the findings of [31] which has highlighted that the entropy is a very appropriate metric to measure the degree of predictability of such sequences.

In this paper, we aim to stress that quantifying the degree of proximity of two nodes joined to the stability of their relationship enables us to enhance the link prediction performance of [8]. For this objective, we redesign the tensor-based link technique by taking into consideration the feedback provided by measuring the link and the proximity at two hops stabilities. Hence, we describe how to quantify the stability and we propose some designs for new prediction metrics.

III. TENSOR-BASED LINK PREDICTION FRAMEWORK

The human mobility patterns highlight correlations in the behavior of network users. The researches done in [11], [3] have emphasized that the human mobility depicts a spatio-temporal regularity and the claims advanced in [2], [4] have demonstrated that social ties characterizing the relationships between users are translated by correlations between human mobility patterns. From the perspective that these relationships govern how the network is structured, the tensor-based link prediction framework aims at identifying and exploiting these correlations to perform prediction. This is made by tracking and quantifying the degree of proximity of each pair of nodes. If two nodes have common intentions at the spatio-temporal level, they tend to be closer to each other and then nearby. Thus, a link occurrence between them is likely.

Predicting future links based on their social closeness is a challenge that is worth an investigation. Indeed, a good link prediction technique contributes to improving the opportunistic forwarding of packets and also enhances the delivery rate and/or decreases latency. Moreover, it helps to avoid situations where packets overload the queue of the nodes that are unable to forward these packets towards their final destinations. Motivated by the enhancement that can provide the prediction to communication protocols, we propose the tensor-based link prediction framework which we describe and explain in this section.

A. Notation

Scalars are denoted by lowercase letters, e.g., a. Vectors are denoted by boldface lowercase letters, e.g., a. Matrices are denoted by boldface capital letters, e.g., A. The $r^{th}$ column of a matrix $A$ is denoted by $a_r$. Higher-order tensors are denoted by bold Euler script letters, e.g., $T$. The $i^{th}$ frontal slice of a tensor $T$ is denoted $T_{i}$. The $i^{th}$ entry of a vector $a$ is denoted by $a(i)$, element $(i, j)$ of a matrix $A$ is denoted by $A(i, j)$.
and element \((i,j,k)\) of a third-order tensor \(\mathcal{T}\) is denoted by \(T_t(i,j,k)\).

### B. Overview on Tensor-Based Link Prediction Technique

In order to quantify the degree of spatial closeness of two nodes, we compute the Katz measure \([20]\). It is used in sociometry and, in the case of wireless networks, expresses the similarity of the behavior (i.e. mobility patterns) or the degree of proximity of two nodes. The Katz measure is dependent on the lengths of paths (one-hop or multi-hop paths) that separate these two nodes. It is computed from a third-order tensor which records the network statistics (i.e. occurrence of links between each pair of nodes during different tracking periods). Hence, a tensor \(\mathcal{Z}\) consists in a set of adjacency matrices which form successive slices. Each slice corresponds to the contacts which occurred during a period of time \(t\) (\(\forall t, 1 \leq t \leq T\) where \(T\) is the total number of periods). Then, we determine a collapsed weighted tensor \(\mathcal{X}\) which allocates weights to the links according to the frequency of their occurrence and their recentness. The use of such a collapsing way is motivated by the results highlighted in \([21]\). Indeed, predicting links in the period \(T+1\) using such a method to aggregate the data achieved best link prediction performance. Applying the Katz measure on the collapsed weighted tensor allows us to obtain the matrix of scores \(S\) which quantifies the behavior similarity or the degree of proximity for each pair of nodes. An example provided by Fig. 1 details how the network structure is tracked and how the prediction scores are determined for the period \(T+1\).

### C. Matrix of Scores Computation

For each node, computing the matrix of scores is performed through two salient steps. Firstly, the link prediction framework records the adjacency matrices in a tensor \(\mathcal{Z}\) and determines the collapsed weighted tensor (or matrix) \(\mathcal{X}\). Secondly, it applies the Katz measure on the matrix \(\mathcal{X}\) to obtain the matrix of Katz scores \(S\).

We consider that the data is collected into the tensor \(\mathcal{Z}\). The slice \(\mathcal{Z}_p(i,j)\) describes the status of a link between a node \(i\) and a node \(j\) during a time period between \([p-1 \cdot t, p \cdot t]\) \((p \in \mathbb{N})\) where \(\mathcal{Z}_p(i,j)\) is 1 if the link exists during the time period \(p\) and 0 otherwise. The tensor is formed by a succession of adjacency matrices \(\mathcal{Z}_1\) to \(\mathcal{Z}_T\) where the subscript letters designate the observed period. To determine the collapsed weighted tensor, we apply the following expression:

\[
\mathcal{X}(i,j) = \sum_{p=1}^{T} (1 - \theta)^{T-p} \mathcal{Z}_p(i,j)
\]

(1)

where the matrix \(\mathcal{X}\) is the collapsed weighted tensor of \(\mathcal{Z}\), and \(\theta\) is a parameter used to adjust the weight of recentness and its value is between 0 and 1.

The matrix \(\mathcal{X}\) can be seen as a generalized adjacency matrix with weighted links. A node can determine the behavior similarity with the other nodes by computing the Katz measure. This similarity between two nodes \(i\) and \(j\) is determined by the length of paths that connect \(i\) to \(j\) and is impacted by the weight of each path length.

Then, Eq. (2) is used to compute matrix of Katz scores \(S\) as following:

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

(2)

where \(\beta\) is a user defined parameter which is strictly positive and \(\beta^{\ell}\) is the weight of a \(\ell\) hops path length. It is clear that the longer the path is, the lower its weight gets. The matrix \(I\) is the identity matrix and \(\mathcal{X}\) is the obtained collapsed weighted tensor.

We depict as previously mentioned in Fig. 1 an example which details the two major steps described before. We take into consideration a network consisting of 4 nodes and having a dynamic topology over 4 time periods and we highlight how similarity scores are obtained (\(\theta\) and \(\beta\) are respectively set to 0.2 and 0.001 for the example and later for the simulations). In this example, we assume that all nodes have the full knowledge of the network structure.

After the investigation into the value to be chosen for the parameter \(\beta\), we found that the convergence of the Katz measure is closely tied to the spectral radius of the adjacency matrix, as mentioned in \([32]\). In fact, \(\beta\) must be greatly inferior to the reverse of the latter value. In our case, we use the collapsed weighted tensor which can be considered as an adjacency matrix with weights of links. After testing the performance of our method through different values of \(\theta\) and \(\beta\), we found that setting \(\theta\) to 0.2 and \(\beta\) to 0.001 enables us to reach one of the highest prediction performances. For more details, we refer the reader to \([33]\) in which we looked at the performance of our framework with different values \(\theta\) and \(\beta\).

### D. Matrix of Scores Interpretation

The social ties between each pair of nodes are quantified by the similarity measure given by \(S(i,j)\). When two nodes share an important score, this means that the paths that connect them tend to be short. Two nodes separated by few hops rimes with a geographical closeness which underlines a correlation.
between their behavior and emphasizes a spatial proximity. Therefore, the link occurrence between these two nodes is strongly plausible. Otherwise, if the similarity score is low or null, the two corresponding nodes share occasional or even no correlation in their behavior.

IV. HOW TO QUANTIFY LINK AND PROXIMITY STABILITIES AND HOW TO USE THEM?

As detailed previously, to predict links in intermittently connected wireless networks, we have used a tensor-based framework to record network structure for a number of periods and have measured Katz scores for each pair of nodes to quantify their behavior similarity. In [8], we have shown that the tensor-based link prediction framework achieves similar performance either when done in a centralized way (i.e. assuming that a central unit records the network statistics and performs prediction) or in a distributed way (i.e. the nodes predict links relying on local information). Obviously, we are interested in the distributed application of the prediction framework as we are concerned by the intermittently connected wireless networks and the effectiveness of our proposal in this case is strongly prominent. Nonetheless, we strongly conceive that we can further improve the prediction efficiency. We think that the prediction becomes more precise if we take into consideration other salient characteristics of ties between nodes. Indeed, we guess that focusing on the stabilities of links and of proximity at two hops are worth investigating and the predictability of human mobility made in [30] has further motivated us to continue in this direction.

A. How Can Link and Proximity Stabilities Improve Link Prediction?

Regarding link stability, when two nodes have strong social ties, a link occurrence between them is likely. If a link between them occurs, it is expected to be persevering and then stable. Indeed, they are expected to be close for a fairly substantial time as they share similar behavior. On the other hand, when the proximity at two hops between two nodes is stable, it can be interpreted in two separate manners. When the stability is expressed by the absence of proximity at two hops, this means that the two nodes are either tied by a link or separated by more than two hops. In this case, the outputs of the tensor-based link prediction technique can be used to identify if the corresponding nodes are directly tied. When this stability is expressed by two nodes constantly separated by two hops, the information provided by the tensor-based link prediction technique is able to attest that a link occurrence is unlikely. Moreover, the corresponding Katz score is expected to be lower than those of pair of nodes having a link between them. If the proximity is unstable, it is obvious to conclude that the link occurrence is unlikely. Indeed, even if there is a link between the two nodes, its occurrence is intermittent and then the link is unstable. The information provided by the Katz measure gives indications about the real state of the link.

Hence, measuring such stability parameters is paramount to enhance the performance of the tensor-based link prediction framework. Therefore, we should refine the tensor-based link prediction framework to make it sensitive to these parameters.

B. Quantifying Link and Proximity Stabilities by Means of Time Series Entropy Estimation

In order to measure these stabilities, we opt for the entropy metric. It is well-known that this measure has been widely used to quantify stability or uncertainty in several domains such as thermodynamics and information theory [33], [34]. For our approach, we have been interested in the entropy estimator used for the Lempel-Ziv data compression [9], [35]. This tool enables us to estimate the entropy of a time series. It has been applied by Song et al. [30] on the sequences of locations visited by several cellular network clients to demonstrate that human mobility is highly predictable. For a record of \( n \) steps, the entropy is estimated by:

\[
S^{est} = \left( \frac{1}{n} \sum_{i} \Lambda_t \right)^{-1} \ln n \tag{3}
\]

where \( \Lambda_t \) is the length of the shortest substring starting at position \( i \) which does not previously appear between position 1 and \( i - 1 \).

Before exploiting this estimator in link prediction, we have to define the time sequences in order to measure the stability of each link. Instead of Song’s et al. approach which consists in filling in the user’s location labels for each step, we rely on statistics of the link state between each pair of nodes. To construct this sequence, each node has to record the state of a link with every detected neighbor and at each period. Tracking the status of each link through a third order tensor accurately achieves this requirement and for each link we obtain a sequence of zeros and/or ones. Therefore, we propose the entropy estimator \( E_{T}^{p}(i, j) \) which quantifies the stability of the link between the nodes \( i \) and \( j \) over \( T \) periods. This is given by:

\[
E_{T}^{p}(i, j) = \left( \frac{1}{n} \sum_{t=1}^{T} \Lambda_t(Z_t(i, j)) \right)^{-1} \ln n \tag{4}
\]

where \( \Lambda_t(Z_t(i, j)) \) is the length of the shortest substring (consisting of a sequence of zeros and/or ones) starting at position \( t \) which does not previously appear between position 1 and \( t - 1 \). The parameter \( n \) corresponds to the number of substrings which are identified.

In the same way, we define \( E_{T}^{p}(i, j) \) as estimator of the entropy which quantifies the stability of the proximity at two hops of the pair of nodes \((i, j)\). It is computed as in Eq. (4) but by substituting, for the value \( Z_t(i, j) \), the state of proximity at two hops at period \( t \) (1 if \( i \) and \( j \) are separated by 2 hops at the period \( t \) and 0 otherwise).

The Lempel-Ziv entropy estimator identifies at each step the shortest sequence which is not detected before. Therefore, we are tracking the length of the substrings step by step. If the shortest substrings become quickly too long, this means that there is redundancy. Indeed, the first chains added in the
The scores are determined by joining the entropy estimations with the tensor-based link prediction technique but combining the collapsed weighted tensor value \( E_{T}^{l}(i, j) \) and the entropy estimation \( E_{X}^{i,j} \). The aim is to demonstrate that measuring the stability and the entropy estimations with the tensor-based link prediction technique are able to determine if the stability is quantified for an occurring tie (series of ones in the tensor) or for a tie that is occasionally or never created (series of zeros in the tensor). Then it is important to combine them to a metric that expresses the lifetime or the perseverance of a link. From this perspective, we propose the combination with the Katz measure and/or the weight provided by the collapsed weighted tensor. Therefore, after evaluating several ways to combine the entropy estimations with the tensor-based link prediction framework, we propose four different techniques to join them. Our aim is to demonstrate that measuring the stability and exploiting it are really beneficial to improve the prediction performance. In this work, we want to prove that considering the stability of ties between nodes improves the link prediction of our framework. We are not seeking the design that ensures the best prediction efficiency. This investigation will be the aim of a future work. In the following, we detail how we design the combinations in order to predict better a link occurrence between a node \( i \) and a node \( j \) through new metrics.

- **Combining the collapsed weighted tensor value \( X(i, j) \) with the link entropy estimation \( E_{T}^{l}(i, j) \) (XE scores):** We suggest to join the entropy estimation \( E_{T}^{l}(i, j) \) (as expressed in Eq. 1) and where \( (i, j) \) is a pair of nodes) to the weight collected by the matrix \( X(i, j) \) (Eq. 1) as we are seeking the most stable occurring links. In other words, we want to identify the links that have high weight and in the same time low estimation of the entropy. We use normalized values for \( E_{T}^{l}(i, j) \) and \( X(i, j) \).

- **Combining the Katz measure \( S(i, j) \) with the link entropy estimation \( E_{T}^{l}(i, j) \) (SE scores):** We proceed as for the previous suggestion but we join the entropy estimation with the behavior similarity metric \( S(i, j) \) (Eq. 2). We aim to check and assess that joining sociometric and stability measures can be helpful to make more precise predictions. As in the previous combination, we use normalized values for both parameters.

- **Computing the Katz measure \( S(i, j) \) from the combination of the collapsed weighted tensor value \( X(i, j) \) with the link entropy estimation \( E_{T}^{l}(i, j) \) (XES scores):** We propose to apply the tensor-based link prediction technique but combining the collapsed weighted tensor \( X \) with the link entropy estimation. Indeed, we combine each weight \( X(i, j) \) (Eq. 1) with the measure \( E_{T}^{l}(i, j) \) (Eq. 4) and we apply the Katz formulation on the described combination in order to obtain a new matrix of scores. Also, we use normalized values for the entropy estimation and the collapsed weighted tensor values.

- **Computing the Katz measure \( S(i, j) \) with the definition of the new collapsed weighted tensor value \( X_{\text{new}}(i, j) \) (XNS scores):** We also propose to apply the tensor-based link prediction technique but with a new collapsed weighted tensor denoted \( X_{\text{new}} \). To determine it, we compute a coefficient, at each period \( p \) and for each pair of nodes \((i, j)\), that combines the occurrence weight obtained from \( X \) (i.e., lifetime and recentness) with the link stability and/or the proximity stability. Afterwards, we apply the Katz formulation on the new collapsed weighted tensor \( X_{\text{new}} \) in order to obtain a new matrix of scores. The matrix \( X_{\text{new}} \) can be expressed in different ways which are detailed in the following.

Among the scores involving the entropy estimation that we have tested, we hold from each category the metric/metrics which highlights/highlight regularity and efficiency for all simulation scenarios. Then, for \( T \) tracking periods, we define the following matrices of scores:

\[
XE_{\text{Score}} = ([1]_{N \times N} - X) \times E_{T}^{l} \tag{5}
\]

\[
SE_{\text{Score}} = ([1]_{N \times N} - S) \times E_{T}^{l} \tag{6}
\]

\[
XES_{\text{Score}} = (1 - \beta \cdot E_{T}^{l} \times ([1]_{N \times N} - X))^{-1} - I \tag{7}
\]

\[
XNS_{\text{Score}} = (1 - \beta \cdot X_{\text{new}})^{-1} - I \tag{8}
\]

where \( N \) is the number of nodes involved in the statistics and, for two nodes \( i \) and \( j \), \( X_{\text{new}}(i, j) \) is given by:

\[
X_{\text{new}}(i, j) = \sum_{t=1}^{T} (1 - \theta)^{(T-t)} \cdot (Z_{t}(i, j) - \max_{t}(E_{t} - E_{t}(i, j))) \tag{9}
\]

The parameter \( E_{t}(i, j) \) and \( \max_{t}(E_{t}) \) respectively correspond to the current entropy estimation (whether for link stability or proximity stability) and the maximum entropy value that we can obtain for \( t \) periods.
We derive three variants of the \textit{XNS\_Score}. When $E^1_t(i,j)$ is used to compute $X_{\text{new}}(i,j)$, we define the measure \textit{XNS1\_Score}. If $E^p_t(i,j)$ is chosen, we express the metric \textit{XNS2\_Score}. In addition, we consider the case in which we compute $X_{\text{new}}(i,j)$ using the link and the proximity stabilities. In this case, we propose the measure \textit{XNS3\_Score} where $X_{\text{new}}(i,j)$ is given by:

$$X_{\text{new}}(i,j) = \sum_{t=1}^{T} (1 - \theta)^{T-t} \cdot (Z_t(i,j) \cdot \max(E_t(i,j)) - E^p_t(i,j)) \cdot \max(E_t(i,j) - E^p_t(i,j))$$

(10)

In the following section, we detail the different scenarios to evaluate all these metrics and assess their ability to achieve better performance in link prediction.

V. SIMULATIONS SCENARIOS AND PERFORMANCE EVALUATION

To evaluate the efficiency of the tensor-based link prediction method joined to the entropy estimations, we consider two real traces. We present them in the following subsection. Then, we analyze the results obtained and we assess the efficiency of our contribution.

A. Simulation Traces

We consider two real traces to evaluate the contribution of the entropy estimations. We exploit them to construct the tensor by generating adjacency matrices with different time periods lengths. We detail, in the following, the traces used for the evaluation:

- **First Trace: MIT Campus trace**: We take the trace of 07/23/02 [36] and consider the events between 8 a.m. and 4 p.m. (8 tracking hours) to build up the tensors. The number of nodes is 646 and the number of locations (i.e. access points) is 174.

- **Second Trace: Dartmouth Campus trace**: We choose the trace of 01/05/06 [37] and construct the tensor slices relying on SYSLOG traces between 8 a.m. and 4 p.m. also. The number of nodes is 1018 and the number of locations (i.e. access points) is 128.

For each scenario (a fixed tracking period length), we track the occurrences of contacts during $T$ periods. We also consider the adjacency matrix corresponding to the period $T+1$ as a benchmark to evaluate the effectiveness of our proposal. We construct tensors for the following period lengths: 5, 10, 30 and 60 minutes. That is to say that we record the network statistics for respectively a number of periods $T$ equal to 96, 48, 16 and 8 slices (for the case where $t=5$ minutes, it is necessary to have 96 periods to cover 8 hours, 48 periods are needed to do the same when $t=10$ minutes, ...). We consider the distributed case for the computation of scores. We assume that each node has the knowledge about its 1-hop and 2-hop neighbors to compute the Katz measure for the tensor-based link prediction technique and the proposed measures of stability.

B. Simulation Results and Performance Analysis

To asses if the proposed metrics enhance the prediction performance of the tensor-based link prediction framework, we consider these evaluation measures:

- **Top Scores Ratio at the period $T+1$ (TSR)**: we compute the number of occurring links in the period $T+1$ (the first period coming after the record of the network statistics). We call the number of existing links $L$. Then, we extract the links having the $L$ highest scores found after applying the prediction technique and determine the percentage of existing links in both sets.

- **Accuracy (ACC)**: this measure is defined in [38] as the ratio of correct prediction (true positive and true negative predictions) over all predictions (true positive, true negative, false positive and false negative predictions). In other words, it is computed by the ratio $\frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$ (see Table I). We identify for each scenario the maximum value of the accuracy which indicates the degree of precision that can reach each prediction metric.

- **F-Measure or balanced F1 score**: the F-measure [39] is the harmonic mean of precision\footnote{represents to the proportion of links with positive prediction (occurring in the future) which are correctly identified [38]. Based on Table II the precision is equal to $\frac{\text{TP}}{\text{TP} + \text{FP}}$. This value is determined according to the deduced accuracy value.} and recall\footnote{quantifies the ratio of correctly identified links over the occurring links in the future [38]. Referring to Table II the recall is defined by the expression $\frac{\text{TP}}{\text{TP} + \text{FN}}$. This value is also computed according to the retained accuracy value.}. The F-Measure is expressed by $\frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$. The higher the F-Measure is, the better the tradeoff of precision and recall gets and the more efficient the prediction metric is.

We compare the prediction efficiency of the proposed prediction metrics with the one of the tensor-based link prediction technique [8] based on the Katz measure. To propose a comprehensive comparison, we also consider well-known prediction metrics presented in the literature. On the one hand, we consider behavioral-based link prediction metrics such as the similarity metric of Thakur et al. [41] and two metrics expressing mobile homophily proposed by Wang et al. in [25]: the spatial cosine similarity and the co-location rate. On the other hand, we take two link prediction metrics based on measuring the degree of proximity such as the Katz measure. They are the Adamic-Adar measure [27] and the Jaccard’s coefficient [28], [29]. All the metrics that we propose are involved in the latter category.

The evaluation metrics are computed for all traces with different tracking periods lengths. Regarding the MIT Campus trace, the results are reported in Fig. 2. For the Dartmouth Campus trace, the prediction results are listed in Fig. 3. For each figure, the plots (a), (b) and (c) respectively represent the top scores ratio in $T+1$, the accuracy (the percentage exceeding 99%) and the F-Measure obtained for each prediction technique with different tracking periods.

The results obtained enable us to attest that the use of the Katz measure has been one of the best choices to perform
prediction through the tensor-based technique. Using this metric achieves better performance than those of the other link prediction metrics proposed in the literature. Hence, the Katz measure is the best metric that we can use to interpret the meaning of the entropy estimations. The other well-known prediction metrics show a lower performance in the context of predicting such links. Indeed, instead of the Katz measure, they quantify the relationship of a pair of nodes without seeing if a direct link connects them. For example, two isolated neighbors (or having few common neighbors) would have a weak score even if they were connected. On the other hand, two other nodes can be 2-hop neighbors and share several common neighbors which means that the score in this case is relatively high even if no link connects the corresponding pair of nodes.

Comparing the performance of the tensor-based link prediction technique with those of the proposed metrics based on link and/or proximity entropy estimations leads us to assess that our proposal of combining our prediction technique with
stability measures is coherent and effective. We remark that for each scenario, there is at least three among the six proposed metrics that achieve better prediction performance (better top scores ratio at $T + 1$, accuracy and F-measure) than the Katz measure. The Katz measure quantifies the social ties between two nodes by a score. Nevertheless, such a score sometimes cannot indicate if the contacts between these two nodes are stable or interspersed over time. The contribution of the entropy estimation is to identify the stable and persistent links but not only them. Also, the entropy allocates low values when a link never or rarely occurs between two nodes (long sequences of 0 for the status of a link). Hence, combining the Katz measure and the entropy estimation enables us to distinguish more clearly a stable link (low entropy estimation and high Katz measure). Such a combination highlights more clearly how nodes are tied which makes the prediction of the topology more efficient in the period $T + 1$.

Considering both traces, we find that it is better to opt for the $SE$, the $XES$ and the $XNS2$ scores when the tracking periods are long (30 and 60 minutes). When these periods are shorter (10 and 5 minutes), the $XNS$ scores (particularly the $XNS3$ score) are the most suitable metrics. In fact, shortening the length of the tensor period leads to obtaining a more precise tracking of the properties of the links (i.e. better distinction between persistent and fleeting links), more faithful estimation of the stability and then more efficient link prediction (more information about the impact of the tracking period length is provided in [8]). Meanwhile, when we use long tensor periods, tracking become less precise as the method considers long and short contact as the same. For example, if we consider a tracking period of 30 minutes, a contact that occurs during all this period is considered as the same as a contact that only lasts a few seconds during the same period (the status of the link is set to 1). It is clear that we lose precision when the contacts tend to be short. Moreover, we divide the historical data into $T$ periods and when the tracking period are longer, the number of total periods $T$ becomes less. Therefore, the sequence of 0 and 1 that characterizes a link over time becomes shorter and tends to be unstable (due to the lack of precision). Afterwards, the Katz measure, as well as the entropy estimation, is less efficient to characterize the relationship between nodes, especially for short contacts.

In these simulations, we have assumed that each node has knowledge about its one-hop and two-hop neighbors. Limiting the local information to one hop is not compromising the performance either of the tensor-based link prediction technique or of the proposed metrics based on entropy estimation. It is true that we are not able, in this case, to compute the $XNS2$ and the $XNS3$ scores. Nevertheless, the Katz measure is no longer affected with this limitation. In fact, we have proved in [8] that the prediction efficiency of the tensor-based link prediction technique achieves similar performance in predicting links in the period $T + 1$ whether the knowledge is limited to one-hop neighbors or extended to the two-hop neighbors. Fig. 4 depicts the Top Scores Ratio in $T + 1$ obtained from the MIT Campus trace when prediction is performed by the Katz measure and by the proposed link stability based measures using only the knowledge of direct neighbors ($XE$, $SE$, $XES$ and $XNS1$ scores). The results confirm the findings cited above: the performance of each prediction technique is similar in both scenarios. Obviously, the contribution of the entropy estimation is always effective.

VI. CONCLUSION

In this paper, we highlighted that the prediction efficiency of the tensor-based technique that we have advanced can be improved by taking into consideration other aspects on top of measuring social closeness. We proposed to make the prediction sensitive to the link and proximity stabilities. We showed that a strong relationship between two nodes matches also with a stable link between them. Indeed, when similar intentions are shared for a period of time, the link between the corresponding individuals is expected to be stable. We also outlined that considering proximity stability can also be beneficial to improving the prediction performance. To express the stability itself, we proposed an entropy estimator inspired from data compression and which converges to the expected value of entropy for a time series. In our case, the time series is the sequence of the state of the links in the adjacency matrices (sequence of zeros and/or ones).

To assess the efficiency of our contribution, we tried to join the stability feedback to the tensor-based link prediction framework through proposing new prediction metrics. We assessed that we can improve the performance of the prediction technique especially when the tensor time period tend to be short. In other words, using shorter tensor periods favors more precise tracking of contacts between nodes, which leads to a better estimation of the entropy estimations and then more faithful link prediction. Above all, we identified, according to the length of tracking period, the set of metrics that can be used to enhance, as much as possible, the performance of the tensor-based link prediction technique.

As future perspectives, it will be interesting to focus on the best combination that we can design in order to reach the highest level of prediction efficiency. In this work, we
have only proposed some metrics to highlight that measuring the stability of ties can be beneficial without seeking the best combination in terms of prediction performance. In addition, it would be challenging to join our contribution with some communication protocols and especially with opportunistic routing protocols. We aspire to verify that the feedback provided by our contribution will improve the performance of such protocols through guiding them in taking better decisions by using link prediction, to forward packets.

ACKNOWLEDGEMENTS

We want to thank wholeheartedly Makhlouf Hadji for his helpful advice.

REFERENCES

[1] A. Chaintreau, P. Hui, J. Crowcroft, C. Diot, R. Gass, and J. Scott, “Impact of human mobility on opportunistic forwarding algorithms,” IEEE Trans. on Mobile Computing, vol. 6, no. 6, pp. 606–620, June 2007.
[2] T. Hossmann, T. Spyropoulos, and F. Legendre, “Social network analysis of human mobility and implications for dtm performance analysis and mobility modeling,” Computer Engineering and Networks Laboratory ETH Zurich, Tech. Rep. 323, July 2016.
[3] W.-J. Hsu, T. Spyropoulos, K. Psounis, and A. Helmy, “Modeling Spatial and Temporal Dependencies of User Mobility in Wireless Mobile Networks,” IEEE/ACM Trans. on Networking, vol. 17, no. 5, pp. 1564–1577, October 2009.
[4] G. S. Thakur, A. Helmy, and 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] S. Yang, X. Yang, C. Zhang, and E. Spyrou, “Using social network mobility for modeling human mobility,” IEEE Network, vol. 24, no. 5, pp. 6–13, 2010.
[6] T. Karagiannis, J.-Y. Le Boudec, and M. Vojnović, “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.
[7] D. Braha and Y. Bar-Yam, “From centrality to temporary fame: Dynamic centrality in complex networks: Research articles,” Complex., vol. 12, pp. 59–63, November 2006.
[8] M.-H. Zayani, V. Gauthier, I. Slama, and D. Zeghlache, “Tensor-based link prediction in intermittently connected wireless networks,” International Journal of Computer and Telecommunications Networking (COMNET), submitted. [Online]. Available: http://arxiv.org/abs/1108.2606
[9] J. Ziv and A. Lempel, “A universal algorithm for sequential data compression,” IEEE Transactions on Information Theory, vol. 23, no. 3, pp. 337–343, 1977.
[10] S. Wasserman and K. Faust, Social Network Analysis: Methods and Applications, M. Granovetter, Ed. Cambridge University Press, 1994.
[11] P. Hui, J. Crowcroft, and 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 and M. Haahr, “Social network analysis for routing in disconnected 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, and F. Legendre, “Know thy neighbor: Towards optimal mapping of contacts to social graphs for dtm routing,” in Proc. of IEEE INFOCOM, march 2010, pp. 1–9.
[14] L. Page, S. Brin, R. Motwani, and T. Winograd, “The PageRank Citation Ranking: Bringing Order to the Web.” Stanford InfoLab., Tech. Rep., 1999.
[15] W. Hwang, T. Kim, M. Ramanathan, and 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, vol. 103, no. 23, pp. 8577–82, June 2006.
[19] G. Palla, I. Derényi, I. Farkas, and T. Vicsek, “Uncovering the overlapping community structure of complex networks in nature and society,” Nature, vol. 435, no. 7043, pp. 814–8, June 2005.
[20] D. Katsaros, N. Dimokas, and L. Tassiulas, “Social network analysis concepts in the design of wireless Ad Hoc network protocols,” IEEE Network, vol. 24, no. 6, pp. 23–29, November 2010.
[21] E. Acar, D. M. Dunlavy, and T. G. Kolda, “Link Prediction on Evolving Data Using Matrix and Tensor Factorizations,” in Proc. of the IEEE International Conference on Data Mining Workshops, December 2009, pp. 262–269.
[22] D. M. Dunlavy, T. G. Kolda, and E. Acar, “Temporal link prediction using matrix and tensor factorizations,” ACM Trans. Knowl. Discov. Data, vol. 5, no. 2, pp. 10:1–10:27, February 2011.
[23] C. Wang, V. Satuluri, and S. Parthasarathy, “Local Probabilistic Models for Link Prediction,” in Proc. of the Seventh IEEE International Conference on Data Mining, (ICDM ’07), October 2007, pp. 322–331.
[24] D. Liben-Nowell and J. Kleinberg, “The link-prediction problem for social networks,” Journal of the American Society for Information Science and Technology, vol. 58, no. 7, pp. 1019–1031, may 2007.
[25] D. Wang, D. Pedreschi, C. Song, F. Giannotti, and A. L. Barabasi, “Human mobility, social ties, and link prediction,” in Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining, ser. KDD ’11. New York, NY, USA: ACM, 2011, pp. 1100–1108.
[26] L. Katz, “A new status index derived from sociometric analysis,” Psychometrika, vol. 18, no. 1, pp. 39–43, March 1953.
[27] L. A. Adamic and E. Adar, “Friends and neighbors on the Web,” Social Networks, vol. 25, no. 3, pp. 211–230, Jul. 2003.
[28] P. Jaccard, “Étude comparative de la distribution florale dans une portion des alpes et des jura,” Bulletin de la Société Vaudoise des Sciences Naturelles, vol. 37, pp. 547–579, 1901.
[29] G. Salton and M. J. McGill, Introduction to Modern Information Retrieval. New York, NY, USA: McGraw-Hill, Inc., 1986.
[30] C. Song, Z. Qu, N. Blumm, and A.-L. Barabási, “Limits of Predictability in Human Mobility,” Science, vol. 327, no. 5968, pp. 1018–1021, February 2010.
[31] N. Navet and S.-H. Chen, “On predictability and profitability: Would gp induced trading rules be sensitive to the observed entropy of time series?” in Natural Computing in Computational Finance, ser. Studies in Computational Intelligence, A. Brabazon and M. O’Neill, Eds. Springer, 2008, vol. 100, pp. 197–210.
[32] M. Franceschet, “Pagerank: standing on the shoulders of giants,” Commun. ACM, vol. 54, no. 6, pp. 92–101, Jun. 2011.
[33] L. Boltzmann, “Über die beziehung zwischen dem zweiten hauptsatz der mechanischen warmetheorie und der wahrscheinlichkeitsrechnung respektive den satzen uber des warmegleichgewicht,” Wien. Ber., vol. 76, pp. 373–435, 1877.
[34] C. E. Shannon, “A mathematical theory of communication,” The Bell Systems Technical Journal, vol. 27, pp. 379–423, 623–656, 1948.
[35] I. Kontoyiannis, P. H. Algoet, Y. M. Suhov, and A. J. Wyner, “Non-parametric entropy estimation for stationary processes and random fields, with applications to english text,” IEEE Transactions on Information Theory, vol. 44, no. 3, pp. 1319–1327, 1998.
[36] M. Balazinska and 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.
[37] “CRAWDAD: A community resource for archiving wireless data at dartmouth,” http://crawdad.cs.dartmouth.edu/.
[38] T. Fawcett, “An introduction to ROC analysis,” Pattern Recognition Letters, vol. 27, no. 8, pp. 861–874, 2006.
[39] C. J. van Rijsbergen, Information Retrieval. Butterworth, 1979.