Relationship Prediction in Dynamic Heterogeneous Information Networks

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Abstract. Most real-world information networks, such as social networks, are heterogeneous and relations between different entities have different semantic meanings. Therefore techniques for link prediction in homogeneous networks cannot be directly applied on heterogeneous ones. On the other hand, works that investigate link prediction in heterogeneous networks, do not necessarily consider network dynamism in sequential time intervals. In this work we propose a technique that leverages a combination of latent and topological meta path-based features to predict a target relationship between two nodes of given types in a dynamic heterogeneous information network. Our results indicates that combining these features helps in building a more accurate predictive model compared to the state of the art techniques. Amin ▶*TBA: experiments and findings.*◀

Keywords: Link prediction · Relationship prediction · Dynamic heterogeneous networks · Social networks · Network topology · Meta path.

1 Introduction

The goal of link prediction in a network graph [16] is to estimate the likelihood of future relationship between two nodes based on the observed graph. Predicting such connections in a network have multiple applications such as recommendation systems [2, 28, 17, 15, 10], network reconstruction [9], node classification [8], or biomedical applications such as predicting protein-protein interactions [14]. Traditional link prediction techniques, such as [16], consider networks to be homogeneous, i.e., graphs with only one type of nodes and edges. However, most real-world networks, such as social networks, scholar networks, patient networks [5] and knowledge graphs [33] are heterogeneous information networks (HINs) [27] and have multiple node and relation types. For example, in a bibliographic network there are nodes of types authors, papers, and venues, and edges of types writes, cites and publishes.

In a HIN relations between different entities carry different semantics. For instance the relationship between two authors are different in meaning when they are co-authors compared to the case that one cites another's paper. Thus techniques for homogeneous networks cannot be directly applied on heterogeneous ones. A few works such as [31, 29] investigated the problem of link/relationship prediction in HINs, however, they do not consider the dynamism of networks and overlook the potential benefits of analyzing a heterogeneous graph as a sequence of network snapshots. To this end, existing work has already shown that in homogenous networks incorporating temporal changes improves link prediction accuracy [41]. Previous work on temporal link prediction scarcely studied HINs and to the best of our knowledge, the problem of relationship prediction for dynamic heterogeneous networks has not been studied before. A dynamic heterogeneous information network (DHIN) is a HIN, where links are associated with timestamps.

In this work we study the problem of predicting relationships in a DHIN, which can be formulated as: *Given a DHIN graph G at t consecutive time intervals, how can we predict the existence of a particular relationship/path between two given nodes at time $t + 1$?*. The major challenge in relationship prediction in DHINs, is how to effectively combine the HIN topology features and inferred latent features that incorporate temporal changes, to give the best performance. Also, the predictive model should be computationally efficient for real-world large-scale networks. To this end, the main contributions of our work include:

- We propose the problem of relationship prediction in a DHIN, and draw a contrast between this problem and existing link prediction techniques that have been proposed for dynamic and heterogeneous networks;
- We present a simple yet effective technique that leverages topological meta path-based and latent features to predict a target relationship between two nodes in a DHIN;
- We empirically evaluate the efficacy and accuracy of our proposed work on two real-world datasets, and the results show X% to Y% improvement compared to the state of the art baselines.

In the rest of the paper, we introduce the preliminaries and problem statement in Section 2, discuss our solutions to the relationship prediction problem in Section 3, explain the details of our empirical experimentation and findings in Section 4, review the related work in Section 5, and finally conclude the paper.

2 Problem Statement

Our work is focused on heterogeneous information network (graphs) that can change and evolve over time. As such, we first formally define the concept of *Dynamic Heterogeneous Information Networks*, as follows:

Definition 1 (Dynamic heterogeneous information network). *A dynamic heterogeneous information network (DHIN) is a directed graph $G = (V, E)$ with a node type mapping function $\phi : V \to \mathcal{A}$ and a link type mapping function $\psi : E \to \mathcal{R}$, where V, E, $\mathcal{A}$, and $\mathcal{R}$ denote sets of nodes, links, node types, and relation types. Each node $v \in V$ belongs to a node type $\phi(v) \in \mathcal{A}$, each link $e \in E$ belongs to a relation $\psi(e) \in \mathcal{R}$, and $|\mathcal{A}| > 1$ and $|\mathcal{R}| > 1$. Also each edge $e = (u, v, t)$ is a temporal edge from a vertex u to a vertex v at time t.* □

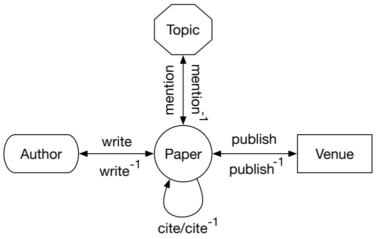


Fig. 1. Network schema for DBLP network.

The DBLP bibliographic network[1] is an example of a DHIN, containing different types of nodes such as papers, authors, topics, and publication venues, with publication links associated with date. Another example is the Twitter social network with nodes types such as tweets, users, topics, and hashtags, and a timestamp associated with these tweets.

In the context of a heterogenous network, a *relation* can be in the form of a *direct link* or an *indirect link*, where an indirect link is a sequence of direct links in the network. Thus, two nodes might not be directly connected, however they might be connected considering the semantic of a sequence of links of different types. In this work, we use the terms *relationship prediction* and *link prediction* interchangeably referring to predicting whether two nodes will be connected in the future via a *sequence of relations* in the graph, where the *length* of a sequence is greater than or equal to one. For instance in a bibliographic network, a direct link exists between an author and a paper she wrote, and an indirect link exists between her and her co-authors through the paper, which they wrote together.In order to better understand different types of nodes and their relation in a network, the concept of *network schema* [31] is used. A network schema is a meta graph structure graph that summarizes a HIN and is formally defined as follows:

Definition 2 (Network schema). *For a heterogeneous network $G = (V, E)$, the network schema $S_G = (\mathcal{A}, \mathcal{R})$ is a directed meta graph where $\mathcal{A}$ is the set of node types in V and $\mathcal{R}$ is the set of relation types in E.* □

Figure 1 shows the network schema for the DBLP bibliographic network with $\mathcal{A}$=\{*Author*, *Paper*, *Venue*, *Topic*\}. In this paper, we refer to different types of nodes in the DBLP bibliographic network with abbreviations P for paper, A for author, T for topic, and V for venue.

Similar to the notion of network schema that provides a meta structure for the network, a *meta path* [31] provides a meta structure for paths between different node types in the network.

Definition 3 (Meta path). *A meta path $\mathcal{P}$ is a path in a network schema graph $S_G = (\mathcal{A}, \mathcal{R})$, denoted by $\mathcal{P}(A_1, A_{n+1}) = A_1 \xrightarrow{R_1} A_2 ... \xrightarrow{R_n} A_{n+1}$, as a*

[1] `http://dblp.uni-trier.de/db/`

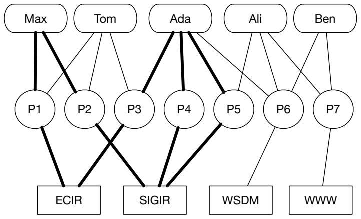


Fig. 2. An example of A–P–V–P–A meta paths between two authors Max and Ada.

sequence of links between node types defining a composite relationship between a node of type A_1 *and one of type* A_{n+1}*, where* $A_i \subseteq \mathcal{A}$ *and* $R_i \subseteq \mathcal{R}$. □

The *length* of a meta path is the number of relations in it. Note that given two node types A_i and A_j, there may exist multiple meta paths of different lengths between them. We call a path $p = (a_1 a_2 ... a_{n+1})$ a *path instance* of a meta path $\mathcal{P} = A_1 - A_2 ... - A_{n+1}$ if $\mathcal{P}$ follows $\mathcal{P}$ in the corresponding HIN, i.e., for each node a_i in $\mathcal{P}$, we have $\phi(a_i) = A_i$. The co-author relationship in DBLP can be described with the meta path $A \xrightarrow{write} P \xrightarrow{write^{-1}} A$ or in short A–P–A. Paths in thick solid lines in Figure 2 correspond to A–P–V–P–A meta paths between *Max* and *Ada*, indicating they published in the same venue, such as *Max–P1–ECIR–P3–Ada*. Each meta path carries different semantics and defines a unique topology representing a special relation.

Meta Path-based Similarity Measures. Given a meta path $\mathcal{P} = (A_i, A_j)$ and a pair of nodes a and b such that $\phi(a) = A_i$ and $\phi(b) = A_j$, several *similarity measures* can be defined between a and b based on the path instances of $\mathcal{P}$. Examples of such similarity or proximity measures in a HIN are *path count* [31, 29], *PathSim* [31] or *normalized path count* [29], *random walk* [29], *HeteSim* [26], and *KnowSim* [34]. Without loss of generality, in this work we use path count as the default similarity measure. For example given the meta path A–P–V–P–A and the HIN in Figure 2, $PC(Max, Ada)$=3 and $PC(Max, Tom)$=3. We now formally define the problem that we target in this work as follows:

Definition 4 (Relationship prediction problem). *Given a DHIN graph* G *at time* t*, and a target relation meta path* $\mathcal{P}(A_i, A_j)$ *between nodes of type* A_i *and* A_j*, we aim to predict the existence of a path instance of* $\mathcal{P}$ *between two given nodes of types* A_i *and* A_j *at time* $t + 1$. □

3 Proposed Relationship Prediction Approach

Given a DHIN graph $G = (V, E)$, we first decompose G to a sequence of t HIN graphs $G_1, .., G_t$ based on links with associated timestamps. We then apply our techniques to predict relationships in G_{t+1}. As mentioned in Definition 4, we intend to predict existence of a given type of relationship (target meta path) between two given nodes. Thus we define a new type of graph, called *augmented reduced graph*, that is generated according to a given heterogeneous network and a target relation meta path.

Definition 5 (Augmented reduced graph). *Given a HIN graph $G = (V, E)$ and a target meta path $\mathcal{P}(A_i, A_j)$ between nodes of type A_i and A_j, an augmented reduced graph $G^{\mathcal{P}} = (V^{\mathcal{P}}, E^{\mathcal{P}})$ is a graph, where $V^{\mathcal{P}} \subseteq V$ and nodes in $V^{\mathcal{P}}$ are of type A_i and A_j, and edges in $E^{\mathcal{P}}$ indicates relationships of type $\mathcal{P}$ in G.* □

For example, an augmented reduced graph for the network in Figure 2 and target meta path $\mathcal{P}(A, A)$=*A–P–V–P–A* is a graph whose nodes are of type *Author* and whose edges represent *publishing in the same venue.*

3.1 Homogenized link prediction

Once the given DHIN graph $G = (V, E)$ is decomposed to t HIN graphs $G_1, .., G_t$, one solution to the relationship prediction problem (Definition 4) is to build an augmented reduced graph $G_i^{\mathcal{P}}$ for each G_i with respect to the given target meta path $\mathcal{P}$ and then predict a link in $G_i^{\mathcal{P}}$ instead of a path in G_i. In other word, we generate a homogenize version of a graph snapshot and apply a link prediction method. The intuition behind considering different snapshots, i.e., a dynamic network, rather than a single snapshot for link prediction is that we can incorporate network evolution pattern to increase the prediction accuracy. Our hypothesis is that the estimated graph $\hat{G}_{i+1}^{\mathcal{P}}$ dependents on $\hat{G}_i^{\mathcal{P}}$. Inspired by the matrix factorization approach presented by Zhu et al. [41] for temporal link prediction in homogeneous networks, we formulate our problem as follows: Given a sequence of augmented reduced graphs $G_1^{\mathcal{P}}, .., G_t^{\mathcal{P}}$, we aim to infer a low rank k-dimensional latent space matrix Z_i for each adjacency matrix $G_i^{\mathcal{P}}$ at time i by minimizing

$$\begin{aligned} &\underset{Z_1,..,Z_t}{\operatorname{argmin}} \sum_{i=1}^{t} \left(\left\| G_i^{\mathcal{P}} - Z_i Z_i^T \right\|_F^2 + \lambda \sum_{x \in V^{\mathcal{P}}} (1 - Z_i(x) Z_{i-1}(x)^T) \right) \\ &\text{subject to} : \forall x \in V^{\mathcal{P}}, i, Z_i \geq 0, Z_i(x) Z_i(x)^T = 1 \end{aligned} \tag{1}$$

where $Z_i(x)$ is a temporal latent vector for node x at time i, $Z_i(x, j)$ indicates the position of x in the j-th dimension, λ is a regularization parameter, and $1 - Z_i(x) Z_{i-1}(x)^T$ penalizes sudden latent position changes for x. This optimization problem can be solved using a gradient descent technique. The intuition behind the above formulation is that nodes with similar latent space representations are more likely to connect, and also nodes move smoothly in the latent space over time and it is less likely to have abrupt moves [39]. The matrix $G_{t+1}^{\mathcal{P}}$ can be then estimated by $\Phi(f(Z_1, ...Z_t))$, where Φ and f are link and temporal functions, ore simply by $Z_t Z_t^T$ as used in [41].

Algorithm 1 gets as input a DHIN graph G, the number of graph snapshots t, a target relation meta path $\mathcal{P}(A, B)$, the latent space dimension k, and the link to predict (a, b) at $t + 1$. It first decomposes G into a sequence of t graphs

Algorithm. 1 Homogenized Link Prediction

```
Input: A DHIN graph $G$, the number of snapshots $t$, a target meta path $\mathcal{P}(A,B)$, the latent space
    dimension $k$, the link to predict $(a,b)$ at $t+1$
Output: The probability of existence of link $(a,b)$ in $G^{\mathcal{P}}_{t+1}$
1: $\{G_1,..,G_t\} \leftarrow DecomposeGraph(G,t)$
2: for each graph $G_i=(V_i,E_i)$ do
3:     for each node $x \in V_i$ that $\phi(x)=A$ do
4:         Follow $\mathcal{P}$ to reach a node $y \in V_i$ that $\phi(y)=B$
5:         Add nodes x and y, and edge $(x,y)$ to the augmented reduced graph $G^{\mathcal{P}}_i$
6:     end for
7: end for
8: $\{Z_1,..,Z_t\} \leftarrow MatrixFactorization(G^{\mathcal{P}}_1,..,G^{\mathcal{P}}_t,k)$
9: Return $Pr((a,b) \in E^{\mathcal{P}}_{t+1}) \leftarrow \sum_{i=1}^{k} Z_t(a,i)Z_t(b,i)$
```

$G_1,..,G_t$ by considering the associated timestamps on edges (line 1). Next from each graph G_i, a corresponding augmented reduced graph $G^{\mathcal{P}}_i$ is generated (lines 2-7) for which nodes are of type a and b (beginning and end of target meta path $\mathcal{P}$). For example given $\mathcal{P}(A,A)$=A–P–A, each $G^{\mathcal{P}}_i$ represents the co-authorship graph at time i. Finally by optimizing the Equation (1) it infers latent spaces $Z_1,...,Z_t$ (line 8) and estimate $G^{\mathcal{P}}_{t+1}$ by $Z_tZ_t^T$ (line 9). Note that Z_i depends on Z_{i-1} as used in the temporal regularization term in Equation (1).

3.2 Dynamic meta path-based relationship prediction

The above homogenized approach does not consider different semantics of meta paths between the source and destination nodes. In fact, Zhu et al. [41] assume that the probability of a link between nodes depends only on their latent positions. On the other hand, Sun et al. [29] proposed a supervised learning framework, called *PathPredict*, that uses meta path-based features in a past time interval to predict the relationship building in a future time interval. It learns coefficients associated with features by maximizing the likelihood of new relationship formation. However, their model is learned based on one past interval and does not consider temporal changes as in [41]. Our intuition is that leveraging meta path-based features along with latent space features can help to boost the prediction accuracy. In other word, we combine latent space features with topological meta path-based features in our predictive model.

Algorithm 2 gets as input a DHIN graph G, the number of graph snapshots t, a network schema S, a target relation meta path $\mathcal{P}(A,B)$, the maximum length of a meta path l, the latent space dimension k, and the link to predict (a,b) at $t+1$. Same as Algorithm 1, it decomposes G into a sequence of graphs (line 1). Next it generates augmented reduced graphs $G^{\mathcal{P}}_i$s from G_is based on $\mathcal{P}$ for which nodes are of type A and B (beginning and end of meta path $\mathcal{P}$) (line 2) as explained in Algorithm 1. It then produces the set of all meta paths between nodes of type A and type B defined in $\mathcal{P}(A,B)$ (line 3). This is done by traversing the network schema S (for instance through a BFS traversal) and generating meta paths with the maximum length of l. It then applies the matrix factorization technique [41] to find latent space matrices Z_i (line 4).On this basis, it then calculates the estimated augmented reduced graph $\hat{G}^{\mathcal{P}}$ at times t and

Algorithm. 2 Dynamic Meta path-based Relationship Prediction

```
Input: A DHIN graph $G$, the number of snapshots $t$, a network schema $S$, a target meta path
    $\mathcal{P}(A, B)$, the maximum length of a meta path $l$, the latent space dimension $k$, the link to
    predict $(a, b)$ at $t + 1$
Output: The probability of existence of link $(a, b)$ in $G^{\mathcal{P}}_{t+1}$
 1: $\{G_1, .., G_t\} \leftarrow \mathit{DecomposeGraph}(G, t)$
 2: Generate target augmented reduced graphs $G^{\mathcal{P}}_1, .., G^{\mathcal{P}}_t$ following Algorithm 1 lines 2-7
 3: $\{\mathcal{P}_1, .., \mathcal{P}_n\} \leftarrow \mathit{GenerateMetaPaths}(S, \mathcal{P}(A, B), l)$
 4: $\{Z_1, .., Z_t\} \leftarrow \mathit{MatrixFactorization}(G^{\mathcal{P}}_1, .., G^{\mathcal{P}}_t, k)$
 5: $\hat{G}^{\mathcal{P}}_t \leftarrow Z_{t-1}Z^T_{t-1}$ and $\hat{G}^{\mathcal{P}}_{t+1} \leftarrow Z_t Z^T_t$
 6: for each pair $(x, y)$, where $x \in V^{\mathcal{P}}_{t-1}$ and $y \in N(x)$ is a nearby neighbor of $x$ in $G^{\mathcal{P}}_{t-1}$ do
 7:     Add feature vector $\langle f^{\mathcal{P}_i}_{t-1}(x, y)$ for $i = 1..n$, $Z_{t-1}(x, j)Z_{t-1}(y, j)$ for $j = 1..k\rangle$ to the training
        set $T$ with $\mathit{label}$=1 if $(x, y)$ is a new link in $E^{\mathcal{P}}_t$ otherwise $\mathit{label}$=0.
 8: end for
 9: $\mathit{model} \leftarrow \mathit{Train}(T)$
10: Return $Pr((a, b) \in E^{\mathcal{P}}_{t+1}) \leftarrow \mathit{Test}(\mathit{model}, \langle f^{\mathcal{P}_i}_t(a, b)$ for $i = 1..n$, $Z_t(a, j)Z_t(b, j)$ for $j = 1..k\rangle)$
```

$t + 1$ (line 5). The last steps create a training dataset for sample pairs (x, y) with feature set containing meta path-based measures $f^{\mathcal{P}_i}_t(x, y)$ for each meta path $\mathcal{P}_i$, and latent features $Z_t(a, j)Z_t(b, j)$ for $j = 1..k$ at time t, and *label*=1 if (x, y) is a new link in $G^{\mathcal{P}}_{t+1}$ otherwise *label*=0 (lines 6-8), subsequently training the predictive model (line 9), generating features for the given pair (a, b) and testing it using the trained model (line 10). In the following section we explain our learning technique in detail.

Combining latent and meta path-based features. Our hypothesis is that combining latent with topological features can increase the prediction accuracy as we can learn latent features that fit the residual of meta path-based features. However, if the latent features learn similar structure to the topological features, then mixing them may not be beneficial. One way to do so is by changing the loss function in Equation (1) to $\operatorname*{argmin}_{\boldsymbol{\theta_i}, Z_i} \sum_{i=1}^{t} \left\| G^{\mathcal{P}}_i - \Phi(Z_i Z^T_i + \sum_{i=1}^{n} \theta_{i_{i-1}} \mathcal{F}^{\mathcal{P}_i}_{i-1}) \right\|^2_F$ and adding another regularization term $\lambda \sum_{i=1}^{t} \sum_{i=1}^{n} \theta^2_{i_i}$, where n is the number of meta path-based features, $\mathcal{F}^{\mathcal{P}_i}$ is the i-th meta path-based feature matrix defined on G_i, and θ_i is the weight for feature f_i. Although the gradient descent algorithm used in the matrix factorization technique to infer latent space matrices in [41] is fast, it cannot be efficiently applied to the changed loss function. This is because it requires computing meta paths for all possible pairs of nodes in $\mathcal{F}^{\mathcal{P}_i}$ for all snapshots, which is not scalable as calculating similarity measures such as PathCount or PathSim can be very costly. For example computing path counts for A–P–V–P–A meta path, can be done by multiply adjacency matrices $AP \times PV \times VP \times PA$.

As an alternative solution, we build a predictive model that considers a linear combination of topological and latent features. These features, however, can be combined in different ways that is beyond the scope of this work. Given the training pairs of nodes and their corresponding meta path-based and latent features, we apply logistic regression to learn the weights associated with these features. We define the probability of forming a *new link* in time $t+1$ from node a to b as $Pr(label = 1|a, b; \boldsymbol{\theta}) = \frac{1}{e^{-z}+1}$, where $z = \sum_{i=1}^{n} \theta_i f_t^{\mathcal{P}_i}(a, b) + \sum_{j=1}^{k} \theta_{n+j} Z_t(a, j) Z_t(b, j)$, and $\theta_1, \theta_2, ..., \theta_n$ and $\theta_{n+1}, \theta_{n+2}, ..., \theta_{n+k}$ are associated weights for meta path-based features and latent features at time t between a and b. Given a training dataset with l instance-label pairs, we use logistic regression with L_2 regularization to estimate the optimal $\boldsymbol{\theta}$ as

$$\hat{\boldsymbol{\theta}} = \operatorname*{argmin}_{\boldsymbol{\theta}} \sum_{i=1}^{l} -logPr(label|a_i, b_i; \boldsymbol{\theta}) + \lambda \sum_{j=1}^{n+k} \theta_j^2 \qquad (2)$$

We preferred to combine features in this learning framework since G_i is very sparse and thus the number of newly formed links are much less compared to all possible links. Consequently calculating meta path-based features for the training dataset is scalable compared to the matrix factorization technique. Moreover, similar to [29], in order to avoid excessive computation of meta path-based measures between nodes that might not be related, we confine samples to pairs that are located in a nearby neighborhood. More specifically, for each source node x in $G_i^{\mathcal{P}}$, we choose target nodes that are within 2-hop of x but not in 1-hop, i.e, are not connected to x in $G_i^{\mathcal{P}}$. We first find all target nodes that make a new relationship with x in $G_{i+1}^{\mathcal{P}}$ and label respective samples as positive. Next we sample an equal number of negative pairs, i.e., those targets that do not make new connection, in order to balance our training set. Once the dataset is built, we perform logistic regression to learn the model and then apply the predictive model to the feature vector for the target link. The output probability can be later interpreted as a binary value based on a user defined cut-off threshold. Amin ▶*in our experiments we evaluate the effectiveness of a training set considering different time intervals and merging of those samples/*◀

3.3 Implementation

We use the implementation of temporal latent space inference for a sequence of dynamic graph snapshots [2][41]. For the classification part, we use the efficient LIBLINEAR [6] package[3] and set the type of solver to L2-regularized logistic regression (primal). We performed 5-fold cross validation for the training phase.

4 Experiments

To assess the efficacy of our proposed technique, we have conduct experiments to address the following research question: *Does combining latent and meta path-based topological features improve relationship prediction accuracy in DHINs?*

[2] https://github.com/linhongseba/Temporal-Network-Embedding

[3] https://github.com/cjlin1/liblinear

4.1 Experiment Setup

Dataset. We conduct our experiments on two real-world datasets that have different characteristics and evolution behaviour.

Publications dataset: The *aminer* citation dataset[4] V8 (2016-07-14) is extracted from DBLP, ACM, and other sources. It contains 3,272,991 papers and 8,466,859 citation relationships for 1,752,443 authors, who published in 10,436 venues, from 1936 to 2016. 78,635 authors had no co-author (about 4%).

179,607 authors had no co-author in 1996-2016. 78,635 authors had no co-author (about 4%). ———— 100,972 (those who published in 1930-1996)?

1,752,443 (total) - 100,972 = 1,651,471 (those who published in 1996-2016)?

1,544,408 authors had no co-author in 1930-1996 78,635 authors had no co-author (about 4%). ———— 1,465,773 (those who published in 1996-2016)?

1,752,443 (total) -1,465,773 = 300,000 (those who published in between)?

Each paper is associated with abstract, authors, year, venue, and title. **Amin** ▶ *We consider only those papers published since 1996, which includes 2,935,679 papers and Y authors.*◀ Authors in [29] used a similar dataset but considered only authors with more than 5 publications. We generate two datasets: one that contains all publications, and one that considers authors with at least 5 papers. We consider $k = 3, 5, and 10$ different time intervals for the dynamic analysis. In our evaluation, we execute the learned model on the last interval to measure the prediction accuracy.

Movies dataset: The RecSys HetRec 2011 movie data set [1] is an extension of MovieLens10M dataset, published by GroupLeans research group [5] that links the movies of MovieLens dataset with their corresponding web pages at Internet Movie Database (IMDB[6]) and Rotten Tomatoes[7] movie review systems. It contains information of 2,113 users, 10,197 movies, 20 movie genres (avg. 2.04 genres per movie), 4,060 directors, 95,321 actors (avg. 22.78 actors per movie), 72 countries, 855,598 ratings (avg. 404.92 ratings per user, and avg. 84.64 ratings per movie), and 13,222 tags (avg. 22.69 tas per user, avg. 8.12 tas per movie).

Movies once release, users can rate them but a paper is published once and new co-authorship is made only at that time... In Publications dataset co-authorship connections are new in Movies dataset new connections to an existing movie. This is a common problem with all rating datasets.

We also conduct our experiments on two variations of the DBLP, one with min 5paper as in ... and one with all.

Experiment Settings. We describe meta paths and target relationships, baseline methods, and different parameter settings.

Baseline methods. (1) *PathPredict* considering only 3 intervals, (2) *BCGD*, (3) regression with *BCGD*, (4) temporal *PathPredict*, (5) hybrid temporal *PathPredict* and *BCGD* (ours).

[4] `https://aminer.org/citation`

[5] `http://www.grouplens.org`

[6] `http://www.imdb.com`

[7] `http://www.rottentomatoes.com`

The state-of-the-art link prediction methods which we compare with our proposed algorithm in these experiments are *PathPredict* [29], and matrix factorization for temporal prediction [41] (denoted as *BCGD*). Sun et al. [29] showed that *PathPredict* is superior to traditional link prediction approaches that use topological features defined in homogeneous networks such as common neighbors [22], preferential attachment [22], Jaccard's coefficient [16], and Katzβ [13]. Their results also indicates that using the path count measure is not considerably different than PathSim or , we consider comparing with path count due to efficiency in meta path-based feature calculation.

For the heterogeneous topological features, we use path count measure for 9 meta paths (denoted as heterogeneous PC) listed in Table II (not including the target relation itself); for homogeneous topological features, we use (1) the number of common coauthors, (2) the rooted PageRank ([7]), and (3) the number of paths between two authors of length no longer than 4, disregarding their different meta paths (denoted as homogeneous PC).

different measures proposed for heterogeneous topological features: the path count (PC), the normalized path count (NPC), (3) the random walk (RW), the symmetric random walk (SRW), and the hybrid of these features.

Their results show that heterogeneous features beat the homogeneous ones (common neighbor, and homogeneous path count), the normalized path count is slightly better that path count, and the hybrid feature produces the best prediction accuracy.

In our experiments we consider only path count as the topological feature due to faster computation and the fact that the results except for the case of hybrid heterogenous features (PC)

higher accuracy and and AUC.

[16]

Therefore in this work we do not compare our proposed technique with such methods.

We consider different number of snapshots (t) to evaluate the effect of timewise data decomposition. The extreme case is having only one graph or having it for each year. Can we find a trade-off?

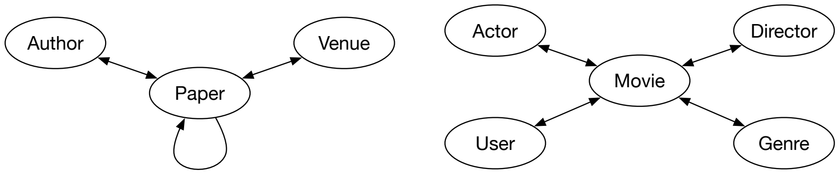
Meta paths and target relationships. Figure 3 depicts network schemas for the two datasets. Note that we consider a simplified version and ignore nodes such as topic fro papers or tag for movies.

We consider .... based on the work in ... we con

Table 1 shows meta paths between authors under length 4 for the publications dataset.

Authors in [29] conducted a case study on a similar DBLP dataset and found that shared co-authors, shared venues, shared topics and co-cited papers for two authors play very significant roles in determining their future collaborations. Similarly we consider meta paths including A–P–A (target meta path), A–P–V–P–A, A–P–A–P–A, and A–P–P–P–A.

We consider different type of target relationship.



(a) Publications Network

(b) Movies Network

Fig. 3. The simplified network schema used for our experiments.

Similarly we only calculated the PC for these meta paths. Note that the goal of our paper is not to select the best features but to show the strength of using...

Table 1. Publications dataset meta paths. V={Author, Paper, Venue}.

Meta path	Meaning
A–P–A	[*The target relation*] Authors are coauthors
A–P–V–P–A	Authors publish in the same venue
A–P–A–P–A	Authors have the same co-author
A–P–P–P–A	Authors cite the same papers

Unlike the A–P–A target relation for the publication dataset for which both ends of the relation is of the same kind, we consider U–M as the target meta path for the movie dataset to show the effectiveness of our proposed methods in predicting such relationships. Amin ▶*The issue with matrix factorization is that originally G_{n*n} is for homogenous network with the same type of nodes. In our case ZZ^T vs. VU^T* ◀

Table 2. Movies dataset meta paths. V={User, Movie, Actor, Director, Genre}.

Meta path	Meaning
U–M	[*The target relation*] A user watches a movie
U–M–A–M	A user watches a movie with the same actor
U–M–D–M	A user watches a movie with the same director
U–M–G–M	A user watches a movie of the same genre
U–M–U–M	A user watches a movie that another user

Parameters. t, k, ...

Evaluation Metrics. To asses the link prediction accuracy, we use Area Under Curves (both Receiver Operating Characteristic (ROC) and Precision-Recall (PR) curves), termed as AUCROC and AUCPR [4]. We also perform the non-parametric McNemar's test [18] to assess the statistical significance of the difference between the accuracy of different classifiers.

4.2 Results and Findings

Adding more features to our Logistic Regression model will increase the training accuracy because model has to consider more data to fit the logistic regression. But testing accuracy increases if feature is found to be significant

The null hypothesis of the McNemar's states that the same population proportion of links will be correctly classified by the two methods. However the test result gives a p-value < 0.0001 and hence we reject the null hypothesis of equal classifier performance.

Amin ►*One reason that A–P–V–P–A is better with intervals is that one may publish in ECIR but there are so many publishing there....*◄

5 Discussion

Applications. Our proposed technique can also be used in other applications. For example link recommendation and predicting missing edges in graphs.

Vertex Recommendation similar to [23]

Combining topological and latent features. Some latent features may be already covered by topological features .... this may affect the accuracy to some extent and that can be done by feature ebgineewring such as bakward...

As shown in [19] and [41], latent features are more predictive of linking behaviour compared to unsupervised scoring techniques such as Katz, Prefferentail Attachemnet, and Adamic.

Experiments in [19] shows combining the latent structure and side-information increases the prediction accuracy.

In this work we modelled the predicted graph $\hat{G}_\tau(i,j)$ as a combination of meta path features and latent features $\Phi(z_i^T z_j + f_D(z_{i,j}; w))$. As explained in [19], one may also augment the model by incorporating some information regarding node affinities using implicit/explicit attributes and define node features x_i, which makes the model $\hat{G}_\tau(i,j) = \Phi(z_i^T z_j + f_D(z_{i,j}; w)$

Link privacy concern. Connection to link privacy research such as [20]

While link prediction techniques has a number of useful applications, it may increase the risk of link disclosure. Even if the data owner removes sensitive links from the published network dataset, it may still be disclosed by link prediction and consequently lead to privacy breach.

Michael et al. [7] presented a link reconstruction attack, in which the attacker uses link prediction to infer a user's connections to others with high accuracy, but they did not mention how to defend the so-called link-reconstruction attack. Since link-reconstruction attack or link-prediction-based attack aims to find out some real but unobservable links, the defense of link-prediction-based attacks is also target-directed, which means that one has to preserve the targeted links from being predicted. In the literature, most existing approaches on link prediction are based on the similarity between pairwise nodes under the assumption that the more similar a pair of nodes are, the more likely a link exists between them.

There is an increasing concern about privacy issues since more and more personal information could be obtained by others online. Many algorithms have been developed for protecting the privacy of users, such as identity, relationship and attributes, from different situations in which different public information was exposed to adversaries [17-20]. In this paper, the focus is on preserving link privacy in social networks.

In retrospect, Zheleva et al. [40] proposed the concept of link re-identification attack, which refers to inferring sensitive relationships from anonymized network data. If the sensitive links can be identified by the released data, then this means privacy breach. Link perturbation is a common technique to preserve sensitive links. Zheleva et al. [40] assumed that the adversary has an accurate probabilistic model for link prediction, and they proposed several heuristic approaches to anonymizing network data. Ying et al. [37] investigated the relationship between the level of link randomization and the possibility to infer the presence of a link in a network. Further, Ying et al. [38] investigated the effect of link randomization on protecting privacy of sensitive links, and they found that similarity indices can be utilized by adversaries to significantly improve the accuracy in predicting sensitive links.

Fard et al. [24] assumed that all links in a network are sensitive, and they proposed to apply subgraph-wise perturbations onto a directed network, which randomize the destination of a link within some subnetworks thereby limiting the link disclosure. Furthermore, they proposed neighborhood randomization to probabilistically randomize the destination of a link within a local neighborhood on a network [20]. It should be noted that both subnetwork-wise perturbation and neighborhood randomization perturb every link in the network based on a certain probability.

To avoid revealing the sensitive information about users, social relationships, link privacy preserving systems provide a delicately perturbed social graph to these applications by adding extra noise to the local structure of a social network. e.g. [11, 21, 37, 40]. The challenge of preserving link privacy lies in causing no significant losses on the utility of applications that leverage the social trust relationships.

6 Related Work

[41] [31] [30] [12] [35] [32] [29] [36] [16]

Matrix factorization technique [19] has been used for link prediction... The link prediction can be seen as a Collaborative filtering problem, where the input is a partially observed matrix of (user, item) preference scores, and the goal is to recommend new items to a user... Collaborative filtering can be seen as a bipartite weighted link prediction problem, where users and items are represented by nodes, and edges between nodes are weighted according to the preference score... the effectiveness of for the structural link prediction problem, inspired by their success in collaborative filtering [?]... as learning latent features from the data, and why it can be expected to be more predictive than popular unsupervised scores.

Such methods are homogeneous and non-temporal. The number of common neighbors [22], preferential attachment [22], Jaccard's coefficient [16], and Katzβ [13], are amongst frequently used topological features defined in homogeneous networks.

Sun et al. proposed PathSelClus [32] that uses limited guidance from users in the form of seeds in some of the clusters and automatically learn the best weights for each meta-path in the clustering process.

The concept of temporal smoothness has been used in evolutionary clustering [36] and link prediction in a dynamic network [41].

There exist many embedding methods for static networks, however very few considered dynamic networks. Zhu et al. [41] attempt dynamic link prediction by adding a temporal-smoothing regularization term to a non-negative matrix factorization objective. Their goal is to reconstruct the adjacency matrix of different time-stamps of a graph. They use a Block-Coordinate Gradient Descent (BCGD) algorithm to perform non-negative factorization. Their formulation is almost identical to the algorithm of Chi et al. [3], who perform evolutionary spectral clustering that captures temporal smoothness. Because matrix factorization provides embedding vectors of the nodes for each time-stamp, the factorization by-product from this work can be considered as dynamic network embeddings.

7 Conclusions and Future Work

TBA.

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