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⌐ ▶*add about our 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 [7] 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, network completion, or biomedical applications such as predicting protein-protein interactions. Traditional link prediction techniques, such as [7], 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 [4] and knowledge graphs [19] are heterogeneous information networks (HINs) [14] 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 [17, 15] 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 [24]. 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.

⃞Amin ▶*For Ebrahim*◄ In this work we study the problem of predicting relationships in a DHIN, which is stated as follows: *Given a DHIN graph G at time t, how can we predict the existence of a particular relationship/path between two given nodes at time $t + 1$?*

The main contributions of our work include:

- We propose the problem of relationship prediction in a DHIN, and analyze the differences between this problem and the related link prediction solutions for dynamic networks and for heterogeneous networks;
- We present a simple yet effective technique that leverages topological meta path-based and latent features to predict a target relationships between two nodes in a DHIN;
- We define the *augmented reduced graph* that is generated according to a given HIN and a target relation meta path and is used in our proposed algorithms: the homogenize link prediction, and the dynamic meta path-based relationship prediction;
- We empirically evaluate the efficacy and accuracy of our proposed algorithms on on two real-world datasets, and the results show X% to Y% improvement in accuracy compared to baseline techniques.

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* [17] 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* [17] 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*

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[1] `http://dblp.uni-trier.de/db/`
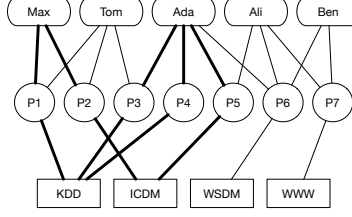
Fig. 2. An example of A–P–V–P–A meta paths between two authors Max and Ada.
Amin ▶change KDD to ECIR◀

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* [17,
15], *PathSim* [17] or *normalized path count* [15], *random walk* [15], *HeteSim* [13],
and KnowSim [20]. More discussion about these similarity measures can be found
in [13, 15, 17]. Without loss of generality, in this work we use path count as the
default 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 $G = (V, E)$, and the number of graph snapshots t Amin
▶*Ebrahim suggested "t subsequent graph snapshots" but I disagree!*◀ , we first decom-
pose 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

| Ebrahim | ▶*Right now, this part is written such that the reader gets a sense that we are only applying an existing method. Can you please rewrite this so that sense is not directly derived by the reader?*◀

Zhu et al. [24] studied the problem of temporal link prediction in the context of homogeneous networks where the input is a sequence of graphs $G_1, ..., G_t$ and the output is the estimated G_{t+1}. They present a matrix factorization (MF) with block-coordinate gradient descent which infers a low rank k-dimensional latent space matrix Z_τ for each adjacency matrix G_τ at time τ by minimizing

$$\underset{Z_1,..,Z_t}{\operatorname{argmin}} \sum_{\tau=1}^{t} \left\| G_\tau - Z_\tau Z_\tau^T \right\|_F^2 + \lambda \sum_{\tau=1}^{t} \sum_u (1 - Z_\tau(u) Z_{\tau-1}(u)^T) \tag{1}$$
$$\text{subject to} : \forall u, \tau, Z_\tau \geq 0, Z_\tau(u) Z_\tau(u)^T = 1$$

where λ is a regularization parameter, and $(1 - Z_\tau(u) Z_{\tau-1}(u)^T)$ penalizes node u for suddenly changing its latent position. $Z_\tau(u)$ is a row vector denoting u's temporal latent space representation at time τ, and $Z_\tau(u, i)$ indicates the position of u in the i-th dimension at Z. The intuition behind their technique is that 1) nodes move smoothly in the latent space over time and it is less likely to have abrupt moves [12, 23], and 2) user interactions are more likely to occur between similar users in a latent space representation. To predict adjacency matrix G_{t+1}, they used $Z_t Z_t^T$, however, they mentioned that G_{t+1} can be formulated as $\Phi(f(Z_1, ...Z_t))$, where Φ and f are link and temporal functions that one may apply techniques such as nonparametric approaches [11] to learn them.

Algorithm 1 is an adaptation of the above MF technique applied on a sequence of augmented reduced graphs $G_i^{\mathcal{P}}$ (Definition 5) given a target meta path $\mathcal{P}$, which changes Equation (1) by replacing G_τ with $G_\tau^{\mathcal{P}}$. The algorithm gets as an 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 $t+1$. The algorithm first decomposes G into a sequence of t graphs $G_1, .., G_t$ by considering the associated timestamps on edges (line 1). Next from

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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 $G_{t+1}^{\mathcal{P}}$
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 $G_i^{\mathcal{P}}$
6:     **end for**
7: **end for**
8: $\{Z_1, .., Z_t\} \leftarrow MatrixFactorization(G_1^{\mathcal{P}}, .., G_t^{\mathcal{P}}, k)$
9: Return $Pr((a, b) \in E_{t+1}^{\mathcal{P}}) \leftarrow \sum_{i=1}^{k} Z_t(a, i) Z_t(b, i)$

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each graph G_i, a corresponding augmented reduced graph $G_i^{\mathcal{P}}$ 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 $G_i^{\mathcal{P}}$ represents the co-authorship graph at time t. Finally the matrix factorization technique in [24] is applied (line 8) to infer latent spaces $Z_1, ..., Z_t$ and estimate $G_{t+1}^{\mathcal{P}}$ by $Z_t Z_t^T$ (line 9). Note that Z_τ depends on $Z_{\tau-1}$ as used in the temporal regularization term in Equation (1).

Amin ▶*Addressed Ebrahim comments till here!*◀

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. [24] assume that the probability of a link between nodes depends only on their latent positions. On the other hand, Sun et al. [15] 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 [24]. 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 $G_i^{\mathcal{P}}$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

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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 $G_{t+1}^{\mathcal{P}}$

1: $\{G_1, .., G_t\} \leftarrow DecomposeGraph(G, t)$
2: Generate target augmented reduced graphs $G_1^{\mathcal{P}}, .., G_t^{\mathcal{P}}$ following Algorithm 1 lines 2-7
3: $\{\mathcal{P}_1, .., \mathcal{P}_n\} \leftarrow GenerateMetaPaths(S, \mathcal{P}(A, B), l)$
4: $\{Z_1, .., Z_t\} \leftarrow MatrixFactorization(G_1^{\mathcal{P}}, .., G_t^{\mathcal{P}}, k)$
5: $\hat{G}_t^{\mathcal{P}} \leftarrow Z_{t-1}Z_{t-1}^T$ and $\hat{G}_{t+1}^{\mathcal{P}} \leftarrow Z_t Z_t^T$
6: **for** each pair (x, y), where $x \in V_{t-1}^{\mathcal{P}}$ and $y \in N(x)$ is a nearby neighbor of x in $G_{t-1}^{\mathcal{P}}$ **do**
7:    Add the feature vector $\langle\ f_{t-1}^{\mathcal{P}_1}(x, y),\ f_{t-1}^{\mathcal{P}_2}(x, y),\ ...,\ f_{t-1}^{\mathcal{P}_n}(x, y),\ \hat{G}_t^{\mathcal{P}}(x, y)\rangle$ to the training set T with $label$=1 if (x, y) is a new link in $E_t^{\mathcal{P}}$ otherwise $label$=0.
8: **end for**
9: $model \leftarrow Train(T)$
10: Return $Pr((a, b) \in E_{t+1}^{\mathcal{P}}) \leftarrow Test(model, \langle\ f_t^{\mathcal{P}_1}(a, b),\ f_t^{\mathcal{P}_2}(a, b),\ ...,\ f_t^{\mathcal{P}_n}(a, b),\ \hat{G}_{t+1}^{\mathcal{P}}(a, b)\rangle)$

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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 MF technique [24] to find latent space matrices Z_i (line 4) and using them calculates the estimated augmented reduced graph $\hat{G}^{\mathcal{P}}$ at times t and $t + 1$ (line 5). The last steps are creating a training dataset with sample pairs (x, y) with feature set containing $\hat{G}_t^{\mathcal{P}}(x, y)$, and meta path-based feature measures $f_t^{\mathcal{P}_i}(x, y)$ based on meta path $\mathcal{P}_i$ at time t, and $label$=1 if (x, y) is a new link in $G_{t+1}^{\mathcal{P}}$ otherwise $label$=0 (lines 6-8), 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 $\underset{\boldsymbol{\theta_\tau}, Z_\tau}{\operatorname{argmin}} \sum_{\tau=1}^{t} \left\| G_\tau^{\mathcal{P}} - \Phi(Z_\tau Z_\tau^T + \sum_{i=1}^{n} \theta_{i_{\tau-1}} \mathcal{F}_{\tau-1}^{\mathcal{P}_i}) \right\|_F^2$ and add another regularization term $\lambda \sum_{\tau=1}^{t} \sum_{i=1}^{n} \theta_{i_\tau}^2$, 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 weights for feature f_i. Although the gradient descent algorithm used in the MF technique to infer latent space matrices in [24] 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 future from node a to b as

$Pr(label = 1 | a, b; \boldsymbol{\theta}) = \frac{1}{e^{-z}+1}$, where $z = \sum\limits_{i=1}^{n} \theta_i f^{\mathcal{P}_i}(a,b) + \sum\limits_{j=1}^{k} \theta_{n+j} Z(a,j) Z(b,j)$,

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 current time 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

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

We preferred combining 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 training dataset is scalable compared to the MF technique. Moreover, similar to [15], in order to avoid excessive computing 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 3-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, 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 $\langle f_t^{\mathcal{P}_1}(a,b), f_t^{\mathcal{P}_2}(a,b), ..., f_t^{\mathcal{P}_n}(a,b), \hat{G}_{t+1}^{\mathcal{P}}(a,b) \rangle$. The output probability can be later interpreted as a binary value based on a user defined cut-off.

3.3 Implementation

Amin ▶*add system and OS spec*◀ We use the implementation of temporal latent space inference for a sequence of dynamic graph snapshots [2][24]. For the classification part, we use the efficient LIBLINEAR [5] package[3] and set the type of solver to L2-regularized logistic regression (primal). We performed 5-fold cross validation for the training phase.

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[2] https://github.com/linhongseba/Temporal-Network-Embedding
[3] https://github.com/cjlin1/liblinear

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?*

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 [15] 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.
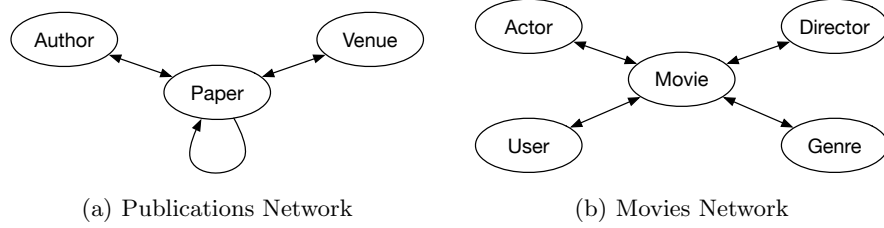- *Movies dataset:* The RecSys HetRec 2011 movie data set [1] is an extension of MovieLens10M dataset, published by GroupLeans research group [5] that links the movies of MovieLens dataset with their corresponding web pages at Internet Movie Database (IMDB[6]) and Rotten Tomatoes[7] movie review systems. 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).

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[4] https://aminer.org/citation
[5] http://www.grouplens.org
[6] http://www.imdb.com
[7] http://www.rottentomatoes.com

(a) Publications Network   (b) Movies Network

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

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. - Parameters

- Baseline methods .Considering the effect of time-wise data decomposition. What if we shorten timespans of each G_t? The extreme is having only one graph or having it for each year. Can we find a trade-off?

– Heterogeneous non-temporal (PathCount, PathSim, NormalPathCount, RandomWalk, SymmetricRandomWalk)
– Homogeneous non-temporal (Katz, Jaccard)
– Homogeneous temporal (BCGD)

- 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 [15] 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.

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...

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

Table 1. Publications dataset meta paths (A = author, P = paper, A = 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

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 (U = user, M = movie, A = actor, D = director, G =g enre).

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

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 [3]. Also in order to decide which classifier has a lower error rate, we perform McNemar's test that assess the significance of the difference between two correlated proportions.

Hi, I have seen various studies use McNemar's test to statistically test the accuracy of several classifications.

McNemar's Test to compare the predictive accuracy of two models. McNemar's test is based on a 2 times 2 contigency table of the two model's predictions.

fMc Nemar?s test [12, 13] is a variant of c2 test and is a non-parametric test used to analyse matched pairs of data. According to Mc Nemar?s test, two algorithms can have 4 possible outcomes arranged in a 22 contingency table [14] as shown in Table 3.

Using this criterion, the z scores are calculated usingMc Nemar?s test for the five classification algorithms. All the algorithms were used with their default parameters as parameter tuning may favor one algorithm to produce better results. The null hypothesis (H0) for this experimental design suggests that different classifiers perform similarly whereas the alternative hypothesis (H1) claims otherwise suggesting that at least one of the classifiers performs differently as shown in Equation 2.

In order to decide which classifier performed better, Ns f and Nf s values for two classifiers are examined. For example, classifier A is said to perform better than classifier B if Ns f is larger than Nf s according to Table 3.

4.2 Results and Findings

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

4.3 Discussion

Our proposed technique can also be used in other applications. For example link recommendation

predicting missing edges in graphs.

Vertex Recommendation similar to [10]

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 [8], 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 $\hat{G}_\tau(i, j) = \Phi(z_i^T z_j + f_D(z_{i,j}; w))$

As shown in [8] and [24], latent features are more predictive of linking behaviour compared to unsupervised scoring techniques such as Katz, PreferentailAttachemnet, and Adamic.

Experiments in [8] shows combining the latent structure and side-information increases the prediction accuracy.

Amin ▶*TODO*◀ Connection to link privacy research such as [9]

From: Target Defense Against Link-Prediction-Based Attacks via Evolutionary Perturbations

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 [25]. It should be noted that both subnetwork-wise perturbation and neighborhood randomization perturb every link in the network based on a certain probability.

As discussed above, link prediction can be applied to predict the potential relationship between two individuals. From another perspective, it may also 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. [26] presented a link reconstruction attack, which is a method that attacker can use 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. Naturally, one can consider finding a way to prevent the link-prediction 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.

In general, since many link prediction algorithms are designed based on network structures, a data owner can add perturbations into the original network to reduce the risk of targeted-link disclosure due to link-prediction-based attacks

From: SmartWalk: Enhancing Social Network Security via Adaptive Random Walks

Extensive research has been carried out to protect the privacy of trust relationships between any pair of users (link privacy) [19, 20, 50, 54, 33, 27]. The challenge of preserving link privacy lies in causing no significant losses on the utility of applications that leverage the social trust relationships. Specifically, link privacy is preserved by adding extra noise to the local structure of a social network. At the same time, global structural characteristics are maintained to ensure that the utility of the social network is not severely reduced. This can be implemented by replacing a real link between two users with a fake link generated by a random walk[33]. Link privacy/utility trade-off. Mittal et al. in [33] considered that the length of random walks for all nodes has a fixed value. As the length increases (more noise), the perturbed social graph converges to a random graph and its utility declines drastically. Our key insight is that instead of adding identical amount of noise to all users, perturbation can be unevenly distributed according to the local mixing time such that privacy can be protected with less perturbation on average. In other words, we can perform nodeadaptive random walks rather than random walks with a fixed length for every user when generating fake links. [33] P. Mittal, C. Papamanthou, and D. Song. Preserving link privacy in social network based systems. In NDSS, 2013

5   Related Work

[24] [17] [16] [6] [21] [18] [15] [22] [7]

Sun et al. proposed PathSelClus [18] 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 [24].

There exist many embedding methods for static networks, however very few considered dynamic networks. Zhu et al. [24] 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. [2], 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.

6   Conclusions and Future Work

TBA.

References

1. Cantador, I., Brusilovsky, P., Kuflik, T.: 2nd workshop on information heterogeneity and fusion in recommender systems (hetrec 2011). In: Proceedings of the 5th ACM conference on Recommender systems. RecSys 2011, ACM, New York, NY, USA (2011)
2. Chi, Y., Song, X., Zhou, D., Hino, K., Tseng, B.L.: Evolutionary spectral clustering by incorporating temporal smoothness. In: Proceedings of the 13th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. pp. 153–162. KDD '07, ACM, New York, NY, USA (2007). https://doi.org/10.1145/1281192.1281212, `http://doi.acm.org/10.1145/1281192.1281212`
3. Davis, J., Goadrich, M.: The relationship between precision-recall and roc curves. In: Proceedings of the 23rd international conference on Machine learning. pp. 233–240. ACM (2006)
4. Denny, J.C.: Mining electronic health records in the genomics era. PLoS computational biology **8**(12), e1002823 (2012)
5. Fan, R.E., Chang, K.W., Hsieh, C.J., Wang, X.R., Lin, C.J.: Liblinear: A library for large linear classification. Journal of machine learning research **9**(Aug), 1871–1874 (2008)
6. Huang, Z., Zheng, Y., Cheng, R., Sun, Y., Mamoulis, N., Li, X.: Meta structure: Computing relevance in large heterogeneous information networks. In: KDD'16 (2016)
7. Liben-Nowell, D., Kleinberg, J.: The link-prediction problem for social networks. journal of the Association for Information Science and Technology **58**(7), 1019–1031 (2007)
8. Menon, A.K., Elkan, C.: Link prediction via matrix factorization. In: Joint european conference on machine learning and knowledge discovery in databases. pp. 437–452. Springer (2011)
9. Milani Fard, A., Wang, K.: Neighborhood randomization for link privacy in social network analysis. World Wide Web **18**(1), 9–32 (2015)
10. Ou, M., Cui, P., Pei, J., Zhang, Z., Zhu, W.: Asymmetric transitivity preserving graph embedding. In: Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining. pp. 1105–1114. ACM (2016)
11. Sarkar, P., Chakrabarti, D., Jordan, M.I.: Nonparametric link prediction in dynamic networks. In: Proceedings of the 29th International Conference on Machine Learning. pp. 1897–1904. ICML'12, Omnipress, USA (2012)
12. Sarkar, P., Moore, A.W.: Dynamic social network analysis using latent space models. ACM SIGKDD Explorations Newsletter **7**(2), 31–40 (2005)
13. Shi, C., Kong, X., Huang, Y., Philip, S.Y., Wu, B.: Hetesim: A general framework for relevance measure in heterogeneous networks. IEEE Trans. Knowl. Data Eng. **26**(10), 2479–2492 (2014)

14. Shi, C., Li, Y., Zhang, J., Sun, Y., Philip, S.Y.: A survey of heterogeneous information network analysis. IEEE Transactions on Knowledge and Data Engineering **29**(1), 17–37 (2017)
15. Sun, Y., Barber, R., Gupta, M., Aggarwal, C.C., Han, J.: Co-author relationship prediction in heterogeneous bibliographic networks. In: Proceedings of the 2011 International Conference on Advances in Social Networks Analysis and Mining. pp. 121–128. ASONAM '11, IEEE Computer Society (2011)
16. Sun, Y., Han, J., Aggarwal, C.C., Chawla, N.V.: When will it happen?: Relationship prediction in heterogeneous information networks. In: Proceedings of the Fifth ACM International Conference on Web Search and Data Mining. pp. 663–672. WSDM '12, ACM, New York, NY, USA (2012)
17. Sun, Y., Han, J., Yan, X., Yu, P.S., Wu, T.: Pathsim: Meta path-based top-k similarity search in heterogeneous information networks. In: Proceedings of the VLDB Endowment 4 (11). pp. 992–1003. VLDB Endowment (2011)
18. Sun, Y., Norick, B., Han, J., Yan, X., Yu, P.S., Yu, X.: Pathselclus: Integrating meta-path selection with user-guided object clustering in heterogeneous information networks. ACM Transactions on Knowledge Discovery from Data (TKDD) **7**(3), 11 (2013)
19. Wang, C., Song, Y., El-Kishky, A., Roth, D., Zhang, M., Han, J.: Incorporating world knowledge to document clustering via heterogeneous information networks. In: Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. pp. 1215–1224. ACM (2015)
20. Wang, C., Song, Y., Li, H., Zhang, M., Han, J.: Text classification with heterogeneous information network kernels. In: AAAI. pp. 2130–2136 (2016)
21. Wang, C., Sun, Y., Song, Y., Han, J., Song, Y., Wang, L., Zhang, M.: Relsim: Relation similarity search in schema-rich heterogeneous information networks (2016)
22. Yang, Y., Chawla, N., Sun, Y., Hani, J.: Predicting links in multi-relational and heterogeneous networks. In: 2012 IEEE 12th International Conference on Data Mining. pp. 755–764 (Dec 2012)
23. Zhang, J., Wang, C., Wang, J., Yu, J.X.: Inferring continuous dynamic social influence and personal preference for temporal behavior prediction. Proceedings of the VLDB Endowment **8**(3), 269–280 (2014)
24. Zhu, L., Guo, D., Yin, J., Steeg, G.V., Galstyan, A.: Scalable temporal latent space inference for link prediction in dynamic social networks. IEEE Transactions on Knowledge and Data Engineering (TKDE) **28**(10), 2765–2777 (Oct 2016)