Type-Aware Anchor Link Prediction across Heterogeneous Networks Based on Graph Attention Network

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Abstract

Anchor Link Prediction (ALP) across heterogeneous networks plays a pivotal role in inter-network applications. The difficulty of anchor link prediction in heterogeneous networks lies in how to consider the factors affecting nodes alignment comprehensively. In recent years, predicting anchor links based on network embedding has become the main trend. For heterogeneous networks, previous anchor link prediction methods first integrate various types of nodes associated with a user node to obtain a fusion embedding vector from global perspective, and then predict anchor links based on the similarity between fusion vectors corresponding with different user nodes. However, the fusion vector ignores effects of the local type information on user nodes alignment. To address the challenge, we propose a novel type-aware anchor link prediction across heterogeneous networks (TALP), which models the effect of type information and fusion information on user nodes alignment from local and global perspective simultaneously. TALP can solve the network embedding and type-aware alignment under a unified optimization framework based on a two-layer graph attention architecture. Through extensive experiments on real heterogeneous network datasets, we demonstrate that TALP significantly outperforms the state-of-the-art methods.

Introduction

Anchor Link Prediction (ALP) aims to recognize the accounts of the same natural person across different networks, and the links between these accounts are anchor links (the accounts are anchor nodes). Anchor links play a pivotal role in inter-network applications, such as user profile modeling (Zhan et al. 2017) and recommendation (Fan et al. 2019; Lu et al. 2016). In reality, these networks (such as social networks, academic networks and movie recommendation networks) are heterogeneous networks, which contain various types of nodes and edges. Predicting anchor link across heterogeneous networks is a research hotspot in the industry and academia at present.

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With the rise of network embedding, anchor link prediction based on embedding has become the mainstream trend. Based on this trend, the core of existing anchor link prediction methods includes two parts: embedding and alignment. The purpose of embedding part is to obtain the representation vectors of network nodes (accounts) based on network embedding method for each network. The alignment part obtains latent anchor links by estimating pairwise similarity between the embedding representation vectors of nodes in different networks. According to whether the two parts are treated separately, the existing methods can be divided into two categories: unified framework approaches (Liu et al. 2016; Shang et al. 2019) and two-stage approaches (Man et al. 2016; Zhou et al. 2018). All the approaches in above two categories are used to predict anchor links across homogeneous networks which contain only one type of nodes and one type of edges.

In practice, however, heterogeneous networks are ubiquitous. At present, there are few methods for anchor link prediction in heterogeneous networks, especially based on network embedding (Wang et al. 2018; Feng et al. 2019). The idea of anchor link prediction in heterogeneous networks is the same as that in homogeneous networks, however, the difference is how to integrate various types of information into the process of embedding and alignment. Previous methods obtain the embedding vector (named fusion vector) of a user node by fusing information of various types of nodes associated with it from global perspective. Then, anchor links
are predicted based on the similarity of fusion vectors. The researchers have verified the effectiveness of their methods, however, there also exist defect: the fusion vector ignores effect of the local type information (information for each type of nodes associated with a user node) on user nodes alignment. This effect is more obvious when there are inconsistent types of nodes in different heterogeneous networks. Take the academic network as an example (Fig.1). $G^S$ contains three types of nodes: author, paper and conference. $G^T$ contains two types of nodes: author and paper. The fusion vector $f_{a1}^S$ of author $a_1$ in $G^S$ contains three types of information, and the fusion vector $f_{a1}^T$ of author $a_1$ in $G^T$ contains only two types of information without conference information. So, the information between $f_{a1}^S$ and $f_{a1}^T$ is inconsistent, which may lead to deviation in estimating their similarity. In addition, for information of author and paper which are included both in $f_{a1}^S$ and $f_{a1}^T$, each type of information has its own impact on user alignment.

To address the above mentioned challenge, in this paper, we propose a unified framework of type-aware anchor link prediction across heterogeneous networks (TALP) based on graph attention architecture. TALP not only considers the effect of fusion vector on users alignment from global perspective, but also considers the impact of type information on alignment from local perspective. All the considering factors are formulated into a single objective function so that minimizing it can allow network embedding and user nodes alignment to be achieved simultaneously in heterogeneous networks.

Specifically, TALP consists of two parts: n-tuple representation and type-aware alignment. For n-tuple representation, we conduct network embedding on each heterogeneous network to lean the n-tuple embedding vectors of each user node. Considering that fusion vectors will lose type information, we use a two-layer Graph Attention architecture (GAT) to learn the fusion vector and type-aware vectors simultaneously. The first layer of GAT aims to integrate the embedding vector which belongs to the same type, and obtain the local representation of the user node on this type information, called type-aware embedding vector. The second layer of GAT aims to fuse different type-aware vectors of the user node to obtain the global embedding vector, called type-fusion embedding vector. For type-aware alignment, we believe that type information and fusion information work together to affect user nodes alignment. In other words, we collaboratively measure the pairwise-similarity of fusion embedding vectors and pairwise-similarity of type-aware embedding vectors, which can guide the n-tuple embedding process.

In a nutshell, the contributions of this paper can be summarized as follows:

- In this paper, we propose a type-aware anchor link prediction framework across heterogeneous networks. This framework predicts anchor links not only based on the pairwise-similarity between type-aware vectors of user nodes, but also considers the pairwise-similarity between type-aware vectors associated with user nodes according to types.

- For anchor link prediction across heterogeneous networks, this paper proposed a unified framework based on graph attention, which can learn n-tuple embedding vectors of each user node while predicting anchor links.

- We evaluate the proposed framework (TALP) on two pairs of real-word heterogeneous networks. The results demonstrate that our method constantly outperforms the state-of-the-art approaches which predict anchor links by only considering the pair-wise similarity between fusion vectors.

### Problem Formulation
In this section, we first introduce concepts in heterogeneous networks, and then introduce the embedding representation of nodes (type-aware embedding and type-fusion embedding). Finally, a formal definition of the type-aware anchor link prediction problem is given.

**Definition 1. Heterogeneous network** A heterogeneous network is defined as a network with multiple types of nodes and/or multiple types of links. It can be denoted as $G = \{V, A, R\}$, where $V$ is a set of nodes, $A$ is a set of links, and $R$ represents the node type union.

Take the heterogeneous network $G^S$ in Fig.1 as an example, $G^S = \{V^S, A^S, R^S\}$, $V^S = \{v_{p1}, v_{p2}, v_{p3}, v_{a1}, v_{a2}, v_{a3}, v_{c1}, v_{c2}\}$, $A^S = \{(v_{a1}, v_{p1}), (v_{a1}, v_{p2}), (v_{a1}, v_{p3}), (v_{a2}, v_{c1}), (v_{a2}, v_{c2}), (v_{a3}, v_{c1}), (v_{a3}, v_{c2})\}$, $R^S = \{p, c, a\}$.

Next, we will take $G^S$ as an example to introduce the type-aware embedding and type-fusion embedding respectively.

**Problem 1. Type-aware embedding**: Given a user node $v_{a1}^S$ in $G^S$ (an author node), $N_{r_{a1}}^S$ represents the set of r-th ($r \in R^S$) type neighborhoods of $v_{a1}^S$. For each node $v_j \in N_{r_{a1}}^S$, its embedding vector is denoted as $\vec{e}_j$, integrating each embedding vector $\vec{e}_j$ ($j = 1, 2, ... |N_{r_{a1}}^S|$) of node in $N_{r_{a1}}^S$ can obtain the type-aware embedding vector of r-th type information of $v_{a1}^S$, denoted as $\vec{w}_{a1}^r$.

**Problem 2. Type-fusion embedding**: Given a user node $v_{a1}^S$ in $G^S$, the type-fusion embedding problem is to integrate
each type-aware embedding vector $\overrightarrow{u}_a^{S_t}$ ($r \in R^S$) associated with $v^{S_t}_a$, denoted as $f^{S_t}_a$.

**Problem 3. Type-aware Anchor link prediction:** Given two heterogeneous networks: $G^S = \{V^S, A^S, R^S\}$ and $G^T = \{V^T, A^T, R^T\}$, $(v^{S_t}_a, v^{T}_{a_j})$ is an anchor link iff $v^{S_t}_a \in V^S$ and $v^{T}_{a_j} \in V^T$ identify the same person here. The representations of $v^{S_t}_a$ and $v^{T}_{a_j}$ are n-tuples containing type-fusion embedding vector and type-aware embedding vectors, denoted as $(f^{S_t}_a, \overrightarrow{u}^{S_t}_a, \ldots)$ and $(f^{T}_{a_j}, \overrightarrow{u}^{T}_{a_j}, \ldots)$, $r \in R^S, g \in R^T$. Type-aware anchor link prediction aims to predict the unobserved anchor links by matching n-tuple representation vectors between each pair of user nodes across $G^S$ and $G^T$.

**Proposed Model**

In this paper, we propose a unified framework TALP to align anchor user nodes across heterogeneous networks, this framework leverages graph attention to help learn the type-aware vectors and type-fusion vector associated with each user node, and obtain the n-tuple representation of each user node. On this basis, we can predict whether there is an anchor link between two user nodes by collaboratively measuring the pairwise-similarity of each element vector in their n-tuple representations.

**n-tuple Representation**

In this section, we use two GAT (Graph Attention Network) to learn n-tuple representation of each user node in $G^S$ and $G^T$ respectively. The parameters in two GATs are shared, taking $G^S$ as an example, we introduce the acquisition process of n-tuple representation for each user node.

**Type-aware Embedding** The GAT we used contains two attention layers: the first layer aims to learn the type-aware embedding and the second layer aims to learn the type-fusion embedding (Fig. 2).

For a user node $v^{S_t}_a$ in $G^S$, we initialize feature vectors of $v^{S_t}_a$ and its each neighbor $v^{T}_{a_j} \in N^T_{v^{S_t}_a}$ to the same dimension $D$ firstly. The initial feature vector is extracted according to information contained in node. Specifically, Word2vec is used for nodes containing text information, and nodes with unclear text information adopt random assignment method to obtain their initial feature vectors. The initial feature vectors of $v^{S_t}_a$ and $v^{T}_{a_j}$ are denoted as $\overrightarrow{x}_i$ and $\overrightarrow{x}_j$ respectively. To learn the $r$-th type-aware embedding vector $\overrightarrow{u}^{S_t}_a$ of $v^{S_t}_a$, we fed all $\overrightarrow{x}_i, 1 \leq j \leq |N^T_{v^{S_t}_a}|$ and $\overrightarrow{x}_j$ into the first attention layer.

Specially, for each node-pair $v^{S_t}_a$ and its arbitrary neighbor $v^{T}_{a_j}$, we first use a linear transformation, parameterized by weight matrix $W^r \in R^{D' \times D'}$, to transfer the initial features into higher-level features, and then compute the importance score of $v^{S_t}_a$ to $v^{S_t}_a$ with self-attention (Vaswani et al. 2017) according to Eq. (1):

$$
\alpha^{r}_{i,j} = \frac{exp(LeakyReLU(W^r_{v^{S_t}_a}[\overrightarrow{w}^{S_t}_{i}]))}{\sum_{i=1}^{|N^T_{v^{S_t}_a}|} exp(LeakyReLU(W^r_{v^{S_t}_a}[\overrightarrow{w}^{S_t}_{i}]))}\tag{2}
$$

where $\cdot^T$ represent transposition, $||$ is the concatenation operation, $\alpha \in R^{D'}$ is a weight vector, $D'$ is the dimension of each type-aware vector.

Then we compute attention coefficient between node $v^{S_t}_a$ and its neighbor $v^{T}_{a_j}$. We inject the adjacency matrix of $G^S$ into the attention mechanism by performing masked attention (Velickovic et al. 2017), and the normalized attention coefficient is expressed as:

$$
\alpha^{r}_{i,j} = \sigma(\sum_{j=1}^{|N^T_{v^{S_t}_a}|} \alpha^{r}_{i,j} W^k \overrightarrow{x}_j)\tag{3}
$$

where $\sigma$ is the Elu activation function.

To stabilize the learning process of self-attention, we employ multi-head attention on computing the type-aware embedding vectors, and $K$ is the number of attention mechanisms. So, we represent the Eq.(3) as a form with multi-head attention mechanisms:

$$
\overrightarrow{u}^{S_t}_a = \sigma(\frac{1}{K} \sum_{k=1}^K \sum_{j=1}^{|N^T_{v^{S_t}_a}|} \alpha^{k,r}_{i,j} W^k \overrightarrow{x}_j)\tag{4}
$$

where $\alpha^{k,r}_{i,j}$ is the normalized attention coefficient computed by the $k$-th attention mechanism, and $W^{k,r}$ is the weighted matrix of $k$-th attention mechanism. In training, K attention mechanisms are independent and parallel.

**Type-fusion Embedding** To obtain the type-fusion embedding vector of $v^{S_t}_a$, we fed all type-aware embedding vectors $\overrightarrow{u}^{S_t}_a (r \in R^S)$ and the initial feature $\overrightarrow{x}_j$ into the second attention layer of GAT, and then aggregate these vectors with attention coefficients.

Specially, for each vector-pair $\overrightarrow{x}_i$ and $\overrightarrow{u}^{S_t}_a$, as their dimensions are different ($D$ and $D'$ respectively), we adopt additive-attention (Bahdanau, Cho, and Bengio 2015) to...
compute attention coefficient between \( \vec{x}_i \) and \( \vec{u}_{ai}^{ST} \). First, the importance score of \( \vec{u}_{ai}^{ST} \) to the type-fusion vector is computed as follows:

\[
q_{i,r} = \vec{m}^T \tanh(W_j \vec{x}_i + W_f \vec{u}_{ai}^{ST})
\]

where \( \vec{m} \in \mathbb{R}^{D''} \) is a weight vector, \( W_j \in \mathbb{R}^{D' \times D} \) and \( W_f \in \mathbb{R}^{D'' \times D'} \) are weight matrices, \( D'' \) is the dimension of the type-fusion vector of \( \vec{v}_{ai}^S \).

The attention coefficient can be computed as:

\[
\beta_{i,r} = \frac{\exp(q_{i,r})}{\sum_{t \in R^S} \exp(q_{i,t})}
\]

The type-fusion embedding vector of \( \vec{v}_{ai}^S \) is denoted as \( \vec{f}_{ai}^S \), and it can be computed according to the following equation:

\[
\vec{f}_{ai}^S = \sum_{r \in R^S} \beta_{i,r} \vec{u}_{ai}^{ST}
\]

So far, we can obtain the \( n \)-tuple representation \( (\vec{f}_{ai}^S, \vec{u}_{ai}^{ST}, \ldots) \) of \( \vec{v}_{ai}^S \), \( r \in R^S \). Similarly, the \( n \)-tuple representation of each user node in \( G^T \) can be obtained. It’s important to note that the weight matrices \( W^{k,r}, W_j \) and \( W_f \) and the weight vector \( \vec{o}, \vec{m} \) are shared in \( G^S \) and \( G^T \), which ensures that the embedding vector tuples of user nodes in two networks are in the same embedding space.

**Type-aware Alignment**

Given two heterogeneous networks \( G^S \) and \( G^T \), \( \vec{v}_{ai}^S \in G^S \) and \( \vec{v}_{ai}^T \in G^T \), if there is an anchor link between \( \vec{v}_{ai}^S \) and \( \vec{v}_{ai}^T \), the embedded vector tuples corresponding to them \( (\vec{f}_{ai}^S, \vec{u}_{ai}^{ST}, \ldots) \) and \( (\vec{f}_{ai}^T, \vec{u}_{ai}^{TT}, \ldots) \) should be as close as possible. Just as important, if \( \vec{v}_{ai}^S \in G^S \) and \( \vec{v}_{ai}^T \in G^T \) do not identify to the same nature person, the distance between their \( n \)-tuple embedding representation should be as far as possible. In other words, the distances between aligned user nodes should be minimized and those of unaligned user nodes should be maximized. In practice, if the types of nodes in two heterogeneous networks are inconsistent, the corresponding type-aware embedding vector in \( n \)-tuple of a user node in this network is supplemented to \( \vec{0} \) when tuples alignment. That is to say, the tuple length must be the same when aligning, as shown in Fig.3. We use \( R^F \) to denote the length of tuple on type-aware alignment, where \( R^F = R^S \cup R^T \).

Therefore, the objective function is:

\[
L = \sum_{(v_{ai}^S, v_{aj}^T) \in B} \sum_{(v_{ai}^S, v_{aj}^T) \notin B} \{\omega [d(\vec{f}_{ai}^S, \vec{f}_{aj}^T) + \xi - d(\vec{u}_{ai}^S, \vec{u}_{aj}^T)] + \lambda [d(\vec{u}_{ai}^S, \vec{u}_{aj}^T)]\}
\]

where \( B \) is the set of known anchor links, \( (v_{ai}^S, v_{aj}^T) \) denote an anchor link and \( (v_{ai}^S, v_{aj}^T) \) is not an anchor link. \( \vec{f}_{ai}^S, \vec{f}_{aj}^T, \vec{f}_{ai}^T, \vec{f}_{aj}^T \) are the type-fusion embedding vector of \( \vec{v}_{ai}^S, \vec{v}_{aj}^T, \vec{v}_{ai}^T \) and \( \vec{v}_{aj}^T \) respectively. \( \vec{u}_{ai}^S, \vec{u}_{aj}^T, \vec{u}_{ai}^T, \vec{u}_{aj}^T \) are their type-aware embedding vector of \( r \)-th type information. \( d(\cdot, \cdot) \) is a distance formula, in this paper \( d(\vec{f}_{ai}^S, \vec{f}_{aj}^T) = ||\vec{f}_{ai}^S - \vec{f}_{aj}^T||_1 \). \( \xi \) is a margin hyper-parameter separating anchor links and unanchored links. \( \omega \) and \( \lambda \) are hyper-parameters balancing the importance between type-fusion similarity and type-aware similarity for anchor link prediction, here, \( \omega + \sum_{r \in R^T} \lambda = 1 \).

**Algorithm 1 The TALP algorithm.**

**Input:** Heterogeneous network \( G^S \) and \( G^T \); Adjacency matrix \( A^S \) and \( A^T \); Anchor links set \( B \); Iteration \( \Gamma \); Hyper-parameter \( \omega, \lambda, \xi, K, D', D'' \)

**Output:** parameter set \( \Theta^* = \{\vec{o}, \vec{m}, W^{k,r}, W_j, W_f\} \);

1. Extract initial feature matrix \( E^S \) and \( E^T \);
2. Learn initial parameter \( \Theta^0 \);
3. Initial \( t \leftarrow 1 \)
4. while \( t < \Gamma \) do
5. \hspace{1em} for \( v_{ai}^S \in G^S \) do
6. \hspace{2em} for \( r \in R^S \) do
7. \hspace{3em} update \( \vec{u}_{ai}^{ST} \) with Eq.(4).
8. \hspace{2em} end for
9. \hspace{1em} end for
10. \hspace{1em} for \( v_{ai}^T \in G^T \) do
11. \hspace{2em} for \( r \in R^T \) do
12. \hspace{3em} update \( \vec{u}_{ai}^{TT} \) with Eq.(4).
13. \hspace{2em} end for
14. \hspace{1em} end for
15. \hspace{1em} end for
16. \hspace{1em} updated \( L \) with Eq.(8)
18. update parameter \( \Theta^t \) with \( L \).
19. \end while

We summarize our algorithm in Algorithm.1. The time complexity of our \( n \)-tuple representation on source and target network are \( O(R^S(|V^S|DD' + |E^S|D')D'') \) and \( O(R^T(|V^T|DD' + |E^T|D')D'') \) respectively, which are linear to the sum number of edges and nodes. Computing embedding vectors of source network and target network are parallel, the time complexity depends on the network with a larger number of nodes and edges. Besides, as the time
complexity of type aware is caused by calculation similarity, which can be ignored. Therefore, the time complexity of TALP mainly depends on the sum of nodes number and edges number in source network or target network.

**Experiment**

**Experiment Setup**

**Datasets and Evaluation Metrics** We conduct our experiment on two pairs of real-word heterogeneous networks: Aminer-Mag and Twitter-Foursquare. Aminer-Mag (Tang et al. 2008) is a pair of citation networks. In Aminer, there are three types of nodes: conference nodes, paper nodes and author nodes, while in Mag, the types of nodes are paper and author. Twitter-Foursquare (Zhang and Yu 2015) is a pair of social networks, the types of nodes in them are user, tweet and location. Table 2 illustrates the statistics of these data sets. We use Precision@k (P@k) and Mean Average Precsion (MAP) (Zhou et al. 2018) to evaluate the performance on ALP.

| Datasets | Nodes | #Nodes | Rel. | #Rel. | #Anc. |
|----------|-------|--------|------|-------|-------|
| Mag      | Auth. | 1,365  | A-P  | 8,348 |       |
|          | Paper | 9,490  | P-P  | 94,312|       |
|          | Loc   | 297,183| U-U  | 164,919|       |
| AMiner   | Auth. | 521    | A-P  | 6,848 |       |
|          | Paper | 8,936  | P-P  | 85,040|       |
|          | Loc   | 3148   | U-U  | 184,919|       |
| Twitter  | User  | 5,520  | U-L  | 164,919|       |
|          | Tweet | 9,490,707| U-T | 9,490,707|       |
| Foursq.  | Tweet | 48,755 | U-T  | 48,756|       |
|          | Loc   | 38,921 | U-L  | 48,756|       |

**Baselines and Settings** We compare our proposed model TALP with the following recent anchor link predicting methods:

- **MAG** (Tan et al. 2014) MAG uses manifold alignment on graph to map users for homogeneous network. The dataset Twitter-Foursquare used in MAG is the same as that in our paper, however the source code of MAG is not public, so in our paper, we directly copy the experimental results reported in MAG to compare with our method.

- **IONE** (Liu et al. 2016) IONE predicts anchor links by learning the followership embedding and followee-ship embedding of a user simultaneously, it is also proposed for homogeneous network. In this paper, for each heterogeneous network, we only keep user nodes and links between them, and input the directed sub-network into to IONE.

- **DeepLink** (Zhou et al. 2018) As a ALP method for homogeneous networks, DeepLink employs unbiased random walk to generate embeddings, and then uses MLP to map users. Similarly to MAG, we directly copy the experimental results reported in DeepLink to compare with our method because of the source code is not public and the shared Twitter-Foursquare datasets between our paper and DeepLink.

- **HAN** (Wang et al. 2019) HAN is a heterogeneous network embedding model which is based on GAT. In this paper, we use it to obtain a embedding vector for each user node in heterogeneous network, and then map user nodes by estimating the pairwise similarity between their embedding vectors.

- **PME** (Chen et al. 2018) PME is also a heterogeneous network embedding method which projects various types of links into different sub-spaces and eventually gets an overall embedding vector for each node. In this paper, we use PME to obtain the embedding vectors and then map them.

- **HHNE** (Wang, Zhang, and Shi 2019) HHNE uses naive active learning to obtain the embedding vector of each node in heterogeneous network. In this paper, we use HHNE to obtain the embedding vectors and then align them.

- **TALP** and **TALP_α** are the variants of TALP. TALP_α only uses the type-fusion embedding vector to align user nodes across heterogeneous networks. TALP_α only uses various types of type-aware embedding vectors to align user nodes. We take them as baseline methods to analyze the importance of type-fusion vector and type-aware embedding vectors for anchor link prediction respectively.

- **TALP_f** and **TALP_α** are the variants of TALP. TALP_f only uses the type-fusion embedding vector to align user nodes across heterogeneous networks. TALP_α only uses various types of type-aware embedding vectors to align user nodes. We take them as baseline methods to analyze the importance of type-fusion vector and type-aware embedding vectors for anchor link prediction respectively.

**Performance Comparison**

In the experiment, all the hyper-parameters of both compared methods and our method TALP are tuned to perform the best on test set. For our model, $D = 300$, $D' = D'' = 128$, $\xi = 3$, $\omega = 0.4$ and $K = 3$, and for all baseline methods we set the parameters the same as original works.

Table 3 gives the convinced results of anchor link prediction. From this table, we can observe that our model TALP consistently outperforms all baselines on two pairs of datasets. More specially:

- TALP is significantly better than previous anchor links prediction methods (HAN, PME, HHNE ) for heterogeneous networks. The reason lies in that previous methods align anchor user nodes only based on the pairwise-similarity of fusion vectors. By comparison, TALP utilizes type-aware embedding vectors and type-fusion embedding vector to align anchor user nodes simultaneously. This precisely shows the effect of type information matching on anchor links. In addition, same as HAN, PME, HHNE, the variant TALP_f also only uses the fusion vector to align users, but its performance are better than them. The reason for this is that our graph attention architecture can better model fusion vectors of user nodes. Meanwhile, HAN, PME and HHNE outperform homogeneous networks ALP methods (MAG, IONE, DeepLink), which indicates that the embedding vector of a user node in heterogeneous network includes richer information than homogeneous networks.

- TALP performs better than TALP_f and TALP_α. For TALP and TALP_f, the only difference between them is whether the matching of type-aware vectors is introduced. Obviously, introducing matching of type-aware vectors can im-
Table 3: Performance comparison on anchor link prediction

| Dataset | Twitter-Foursquare | Aminer-Mag |
|---------|--------------------|------------|
|         | **P@1** | **P@5** | **P@9** | **P@21** | **P@30** | **MAP@30** | **P@1** | **P@5** | **P@9** | **P@21** | **P@30** | **MAP@30** |
| MAG     | 6.38     | 13.62    | 17.05    | 27.08    | 32.29     | -          | 34.18    | 39.27    | 49.56    | 57.81    | 63.42     | 39.19      |
| IONE    | 22.38    | 40.33    | 46.38    | 55.71    | 59.70     | 32.79      | 34.18    | 39.27    | 49.56    | 57.81    | 63.42     | 39.19      |
| DeepLink| 34.47    | 59.42    | 66.09    | 70.00    | 70.48     | 47.78      | 42.65    | 65.81    | 73.92    | 75.34    | 81.96     | 55.96      |
| HAN     | 38.69    | 60.38    | 71.16    | 75.49    | 78.33     | 50.22      | 45.91    | 64.33    | 70.27    | 76.91    | 80.16     | 53.25      |
| PME     | 38.72    | 60.45    | 69.92    | 75.96    | 79.13     | 51.28      | 42.65    | 65.81    | 73.92    | 75.34    | 81.96     | 55.96      |
| HHNE    | 40.51    | 59.89    | 73.18    | 78.54    | 78.54     | 52.42      | 42.65    | 65.81    | 73.92    | 75.34    | 81.96     | 55.96      |
| PME     | 42.66    | 62.32    | 88.50    | 90.40    | 93.79     | 55.89      | 50.56    | 70.34    | 90.07    | 95.23    | 97.68     | 66.25      |
| HAN     | 43.37    | 69.82    | 89.96    | 92.57    | 94.27     | 57.68      | 63.85    | 76.49    | 95.72    | 95.23    | 98.81     | 79.49      |
| HHNE    | 43.79    | 72.32    | 93.22    | 95.20    | 98.69     | 59.33      | 71.19    | 77.68    | 96.32    | 96.89    | 99.87     | 82.39      |

Figure 4: Performance of TALP on different $(1 - \omega)$

prove the performance of anchor user nodes alignment. For TALP and TALP$_a$, the difference between them is whether the matching of fusion vectors is introduced. From table 2, we can see clearly that TALP is better than TALP$_a$, showing that type-fusion information is also beneficial for ALP.

- TALP$_a$ outperforms TALP$_f$. By contrast, TALP$_a$ has better performance than TALP$_f$, which indicates that type-aware information is more efficient than information of type-fusion for anchor links prediction across heterogeneous networks.

- The performance improvement on Aminer-Mag is obviously higher than Twitter-Foursquare. The difference between the two pairs of datasets is that the data types of Aminer and Mag are inconsistent. This proves that our model TALP can better predict anchor links in heterogeneous networks with inconsistent data types.

Discussion

In this section, we evaluate how different choices of parameters affect our model’s performance. In the following experiments, except for the parameter being tested, the rest parameter are set as the optimal configurations.

Performance on different $\omega$ and $\lambda^r$ In our model, $\omega$ is to weight the importance of type-fusion similarity for ALP, and $\lambda^r$ is to weight the importance of $r$-th type-aware similarity for ALP. As $\omega + \sum_{r \in R} \lambda^r = 1$, we only evaluate the effect of the change in $\omega$ on alignment performance of TALP. From Fig.4, we found that (1) TALP achieves the worst performance under $(1 - \omega = 0)$ setting, which indicates that only using type-fusion similarity ($\omega = 1$) is not enough for anchor link prediction, it is necessary to introduce type-aware information; (2) With the growth of $(1 - \omega)$, the performance of TALP increase firstly, which indicates that type-aware information indeed can predict anchor links more accurately. However, with $(1 - \omega)$ further increase, the performance drops gradually, and this shows that it is very important to balance the information of type-aware and the information of type-fusion.

Performance on different $K$ For learning type-aware vectors, we use multi-head attention mechanism. The number of head $K$ also affect the performance on anchor links prediction. From Fig.5, we can see that TALP, TALP$_a$, and TALP$_f$ on two pairs of datasets achieve the best performance when $K = 3$, indicating that $K = 3$ best express the type-aware information of user nodes and delivers alignment characteristics of user nodes across heterogeneous networks. The performance on all datasets begins to gradually rise to the highest point and then declines as the number of head $K$ grows. This mainly because that too small $K$ can not capture the richer type-aware information and larger $K$ may introduce noisy.

Performance on different training ratio For different training-to-test ratios, as observed from Fig.6(a) and Fig.7(a), TALP outperforms all the baselines on two pairs of datasets. Even for the ratio as low as 10% to 20%, the performance of them still superior to the baselines. In addition, TALP, TALP$_a$, and TALP$_f$ achieve best results when
the ratio rose to 70% while other baselines achieve good performance when the training ratio is around 90%, which demonstrates the robustness of our model.

**Performance on different embedding dimension** For different embedding dimension, according to Fig.6(b) and Fig.7(b), we observe that a low dimensionality is sufficient for all the methods except MAG. It is well known that the complexity of the learning algorithm is highly dependent on spatial dimensions. In this paper, we select 128 as the optimal dimension.

**Performance on different training iteration** Fig.6(c) and Fig.7(c) show how the performance of our model and baselines methods changes with different training iterations. We observe that the performance of all the methods consistently achieve better results as the iteration number increases. The number of training iterations reflects the convergence speed of algorithms. TALP converges to the best result sooner than all baselines.

**A case study**

To better understand and gain deeper insights into the effect of node type information difference on alignment process, we randomly sample two pairs of real anchor users and show their neighbors in Fig.8. The yellow and white rows represent Aminer and Mag datasets respectively. In particular, we observe that:

- **Type-aware alignment could predict anchor users that type-fusion method can not.** For the neighbors of paper type, user “I**r Ivanov” has both the same papers and different papers in two datasets. The role of different papers will be magnified. For example, “I**r Ivanov” links a paper “5-Selenization of salicylic acid ***” in Aminer but links another paper “Experimental ionization of atomic ***” in Mag. This difference leads to the similarity of this user’s type-fusion vectors in two datasets are only 0.49, which is hard to determine whether there exists an anchor link. By comparison, considering type information difference with type-aware method, the similarity is 0.61, which makes it easier to determine an anchor link. This again verifies why our method can improve alignment precision.

- **For the anchor links that can be predicted by both methods, type-aware alignment achieves higher similarity than that of type-fusion.** Although user “E**er Zartzer” has the same paper information in two datasets, the author information is different. In specific, author “A**sM. Yinnon” in Aminer is different from that in Mag (“A**s.s.M. Yinnon”). Besides, conference information in Mag is “NULL” which is different from that in Aminer. Type-fusion method ignores these type information differences which was focused on by the type-aware method, so the similarity between anchor users are lower.

**Related Work**

**Heterogeneous Network Embedding**

Heterogeneous network embedding refers to learning representation of nodes/edges in heterogeneous network. In re-
cent years, many researchers have done a lot of work in this area. PME (Chen et al. 2018) and (Sun, Zhao, and Liu 2015) project various relations into different embedding subspace and then map them into the same embedding space via translation or coordinate matrix. HAN (Wang et al. 2019) provides a meta-path based GAT model to learn the embedding vectors through node-level and semantic-level attention mechanism. EGNN (Gong and Cheng 2018) jointly encodes both nodes and edges into an unified low-dimensional space via GCN. GaAN (Zhang et al. 2018) apply attention mechanism into gated neural network to solve node classification problem. Unlike the traditional multi-head attention mechanism, which equally consumes all attention heads, GaAN uses a convolution sub-network to control the importance of each attention head. EOE(Xu et al. 2017) learns the embedding representation of two networks, and incorporates a harmonious embedding matrix to transform the representation of different networks into the same space.

**Anchor Link Prediction**

The traditional ALP methods mainly compute pair-wise similarity based on well-design hand-crafted features, for example, MNA (Kong, Zhang, and Yu 2013) extracts features from the social structural and text content information. (Koutra, Tong, and Lubensky 2013) extracts features form various node attributes, e.g., user-name, typing patterns and language patterns, etc. Though achieving great performance, they are time-consuming, labor expensive and usually suffer from inflexible extension.

Different from the above hand-crafted features methods, the embedding based methods could learn node’s features automated, which includes embedding and alignment parts. According to whether the two parts are treated separately, existing methods can be divided into two categories: the first category is to predict anchor links by taking those two parts as two independent steps, such as PALE (Man et al. 2016) firstly learns network embedding via capturing each node’s major structural regularity, and then learning a mapping function across the two learned low-dimensional spaces. DeepLink (Zhou et al. 2018) samples the networks and learns to encode network nodes into vector representation to capture local and global network structures which, in turn, can be used to align anchor nodes through deep neural networks. The second category is to solve embedding and alignment problem simultaneously based on a unified framework. For example, IONE (Liu et al. 2016) considers both follower/followee-ship in network and anchor users across networks via formulating them into a single objective function. PAAE (Shang et al. 2019) devices an auto-encoder to capture major structural regularity in one network via an adversarial regularization and then formulates both embedding and alignment problem into a single objective function.

Besides, there are some works about anchor link prediction across heterogeneous networks. LHNE (Wang et al. 2018) embeds cross-network structural and content information into a unified space by jointly capturing the friend-based and interest-based user co-occurrence in intra-network and inter-network, respectively. And then align users based on those embedding vectors. DPLink (Feng et al. 2019) proposes an end-to-end deep neural network, which solves anchor link prediction based on heterogeneous mobile data collected from services with different natures.

**Conclusion**

In this paper, we present a type-aware anchor link prediction framework across heterogeneous networks, which considers the effects of the local type information on user nodes alignment. This framework predicts anchor links not only based on the pairwise-similarity between type-fusion vectors of user nodes, but also considering the pairwise-similarity between type-aware vectors of different types of nodes associated with user nodes. For each user node, TALP can learn a n-tuple representation based on two-layer graph attention architecture. Anchors are used to supervise the objective function which aims to minimizing the distance between anchors. On this basis, we can predict whether there is an anchor link between two user nodes via measuring the pairwise-similarity of each element vector in their n-tuple representations. Experiments on real-world heterogeneous network datasets demonstrate the effectiveness and
efficiency of TALP. In future, we plan to extend our model to anchor link prediction across multiple (more than two) heterogeneous networks.

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