INAMA: An Interactive Attentional Model for Node Alignment

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Abstract

Because of wide studies of Social Network Analysis (SNA), identifying users from heterogeneous platforms, also known as node alignment, has gradually become a research hotspot. In this paper, we propose an **IN**teractive **A**ttentional **M**odel for Node **A**lignment, namely *INAMA*. To tackle the issue, the model leverages both topology structures and node attributes. First, we define the *matched neighbors* instead of the original topology structures, which consist of neighbors from the aligned pairs. By doing so, our model can efficiently leverage topology information. Then, an interactive attentional model is built to model node message passing processes. Specifically, intra and inter attentional mechanisms are introduced to determine the neighbor influences from local and across networks, respectively. Finally, we evaluate our model on six real-world datasets and the experimental results demonstrate the effectiveness of our model.

Keywords: Node alignment, Interactive attentional model, Matched neighbors, Intra and inter

1 Introduction

With the development of the Internet, various social networks are around people's lives. Usually, these social networks are built from heterogenous platforms. Thus, the same person would have different friendships and user profiles. Identifying whether two users from different platforms are the same becomes a hotspot in SNA. The issue is also known as node alignment and addressing it could serve many downstream tasks, such as cross-domain recommendation [1-2] and link prediction [3-4].

Previous efforts usually addressed the issue by comparing node attribute similarities, such as genders, names and affiliations [5-9]. Although these methods look sound, node attributes from different platforms are usually quite different or fake. Therefore, only utilizing node attributes would not give sufficient clues for node alignment. To better understand it, we show an example of *Twitter-Instagram* subnetworks in Figure 1, where the goal is to identify whether v_1 and u_1 are the same. Because '*WADE*' is a common surname, only comparing '*dwyanewade*' and '*DWade*' cannot give a high confidence to align them. As we know, graph-structured datasets usually consist of node attributes and topologies. In other words, comparing topology similarities is also a common way. As shown in Figure 1, (v_2, u_2) and (v_4, u_4) are two aligned pairs, which have the same names and link to the candidate pair (v_1, u_1). Thus, there exists similar topologies of v_1 and u_1, which can help us to infer v_1 and u_1 having a high possibility of being aligned. For example, IONE [10] and PALE [11] are two representative methods, which align nodes by encoding topologies into deep latent spaces. However, both methods ignore rich node attributes. Benefitting from attributed network embedding [12], many attempts have emerged to incorporate both node attributes and topologies for node alignment. Such as [13] and [14], both of them leverage the two aspects but still have some drawbacks, where they only aggregate node embeddings with the local topologies but node alignment is an interactive task across networks. Therefore, both of them cannot learn message passing processes across networks, and existing methods lack aggregating interactive neighbor information for node alignment.

In this paper, we present the INAMA model, which leverages both node attributes and topologies for node alignment. Different from previous studies, our model designs an interactive attentional framework to aggregate diverse neighbor information. Specifically, we first define matched neighbors instead of original topologies, which only preserve neighbors from aligned pairs. Next, intra and inter attentional mechanisms are introduced to aggregate interactive neighbor information, where intra and inter attentions

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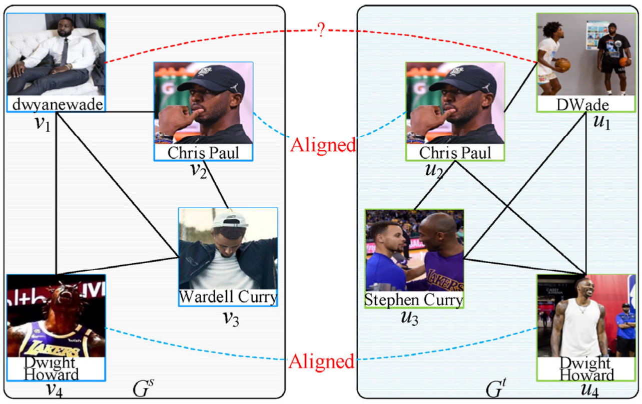


Figure 1. An example of node alignment, where black lines denote connections, the aligned pairs are linked by blue dashed lines and the candidate pair is (v_1, u_1)

are with respect to (*w.r.t*) the aggregating operators for neighbors from local and across networks. Finally, a supervised deep model is applied to generate the probabilities for each candidate pair. The main contributions are as follows:

- Because of leveraging aligned pairs, our method benefits from matched neighbors in two folds: (i) The error propagations by noisy neighbors are reduced; (ii) The scales of inputs are decreased.
- To incorporate the interactive neighbors, intra and inter attentional mechanisms are proposed. By doing so, it can model neighbor influences from local and across networks, respectively. The attentional results can nicely fit to the supervised deep model.
- We compare our method with several state-of-the-art baselines on six real-world datasets. Results show our method of delivering promising performances.
- As a further exploration of our previous work [15], we conduct the Friedman Test [16] and the post-hoc Nemenyi Test [17] to investigate whether INAMA has statistical differences with other basslines. The results show that our method significantly beats KNN and SVM.
- Ablation studies are also included in our experiments, and results show all components contribute to our method.

The rest of this paper is as follows: Sec. 2 describes the node alignment problem. In Sec. 3, we detail the matched neighbors and proposed model. Experimental results are presented and discussed in Sec. 4. Sec. 5 briefly reviews the existing approaches for node alignment, and conclusions are made in Sec. 6.

2 Problem Formulation

Let $G^s = (V, E^s, X^s)$ and $G^t = (U, E^t, X^t)$ be the source and target networks, where V and U are node sets, E^s and E^t are connection sets, X^s and X^t denote node attributes. Given a candidate pair (v, u), where $v \in V$ and $u \in U$. We can formulate the node alignment problem as follows:

$$f : (v, u, E_v^s, E_u^t, X_v^s, X_u^t) \to \hat{y}, \quad \textbf{(1)}$$

where f represents the mapping function, E_v^s and E_u^t represent the topologies of v and u, X_v^s and X_u^t represent the attributes of v and u, $\hat{y}$ represents the predicted result. Therefore, the essence of node alignment is to find a suitable mapping function *f*.

3 The Proposed Method

In this section, we show the details of the proposed model. First, we define the matched neighbors. Then, we build an interactive attentional model upon the matched neighbors.

3.1 Matched Neighbors

Because topologies in source and target networks are usually heterogeneous, adopting original neighbors of the candidate pair may bring some noises. To overcome it, we define matched neighbors instead of the original ones. Assuming there's a candidate pair (v, u) and R aligned pairs $\langle A^s, A^t \rangle$, where $v \in V$, $u \in U$, $A^s \subseteq V$, $A^t \subseteq U$ and (A_i^s, A_i^t) represents the *i-th* aligned pair. First, we augment topology structures through aligned pairs. Given any two aligned pairs (A_i^s, A_i^t) and (A_j^s, A_j^t), we link A_i^t to A_j^t if A_i^s linking to A_j^s, and link A_i^s and A_j^s if A_i^t linking to A_j^t. Then, we can obtain the neighbors N_v^s and N_u^t for v and u. Next, we intersect neighbors and aligned sets for v and u. To avoid empty sets, we add each node itself to the results of intersections to generate corresponding matched neighbors. The detailed process is shown in Algorithm 1.

Algorithm 1. Generating Matched Neighbors

Input: $v \in V$, $u \in U$, $A^s \subseteq V$, $A^t \subseteq U$.
1. **for** $i = 1, ..., R$ **do**
2. **for** $j = 1, ..., R$ **do**
3. **if** A_i^s *linking to* A_j^s (A_i^t *linking to* A_j^t):
4. let A_i^t *link to* A_j^t (A_i^s *link to* A_j^s)
5. **end if**
6. **end for**
7. **end for**
8. generating neighbors N_v^s and N_u^t *w.r.t* v and u
9. $M_v = N_v^s \cap A^s \cup v$, $M_u = N_u^t \cap A^t \cup u$

Output: $M_v = [v_1, \ldots, v_P]$, $M_u = [u_1, \ldots, u_Q]$.

To better understand the definition, we review Figure 1 and show how to generate matched neighbors for the candidate pair (v_1, u_1) in Figure 2. We first augment the original topologies and connect v_4 to v_2 with a red line. It is clear that v_1 and u_1 have similar triangles $\blacktriangle(v_1, v_2, v_4)$ and $\blacktriangle(u_1, u_2, u_4)$, which implies v_1 and u_1 have a high confidence to be aligned. Next, we generate neighbors for v_1 and u_1 as $N^s_{v_1} = [v_2, v_3, v_4]$ and $N^t_{u_1} = [u_2, u_3, u_4]$. Finally, after several set operations, we can obtain the matched neighbors of v_1 and u_1 as $M_{v_1} = [v_1, v_2, v_4]$ and $M_{u_1} = [u_1, u_2, u_4]$.

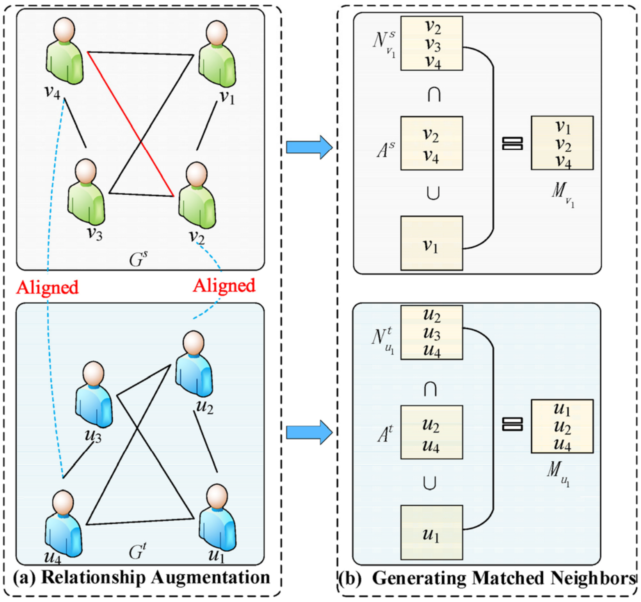


Figure 2. An example of generating matched neighbors for v_1 and u_1

3.2 INAMA Model

Based on the matched neighbors and node attributes, an interactive attentional model INAMA is built, where intra and inter attentional mechanisms reflect the interactions. Figure 3 shows the overall framework, where Figure 3(a) presents the main model and Figure 3(b) gives the employed attentional mechanism. According to Figure 3(a), our model consists of four components: (1) First, employing an embedding layer to obtain dense low dimensional embeddings; (2) Then, adopting intra and inter attentions to aggregate the interactive neighbor information of the candidate pair; (3) Next, several hidden layers are utilized; (4) Finally, the output is given to determine whether the candidate pair is matched.

Without loss of generality, assuming the candidate pair is (v, u) and their corresponding matched neighbors are $M_v = [v_1, \ldots, v_P]$ and $M_u = [u_1, \ldots, u_Q]$. Given any node z and its original attribute $X_z \in \mathbb{R}^F$, where F represents the original dimension of attributes. Through embedding layer, we can map X_z into a d dimensional dense embedding $h_z \in \mathbb{R}^d$ as follows:

$$h_z = \tanh\left(W^T X_z + b\right), \qquad \textbf{(2)}$$

where $W \in \mathbb{R}^{F \times d}$ is a sharing weighted matrix and $b \in \mathbb{R}^d$ is the corresponding bias. In particular, the *tanh* function is adopted. According to Eq. 2, we can obtain embeddings of the candidate pair as h_v and h_u, and embeddings of their corresponding matched neighbors as $\left[h_{v_1}, \ldots, h_{v_P}\right]$ and $\left[h_{u_1}, \ldots, h_{u_Q}\right]$.

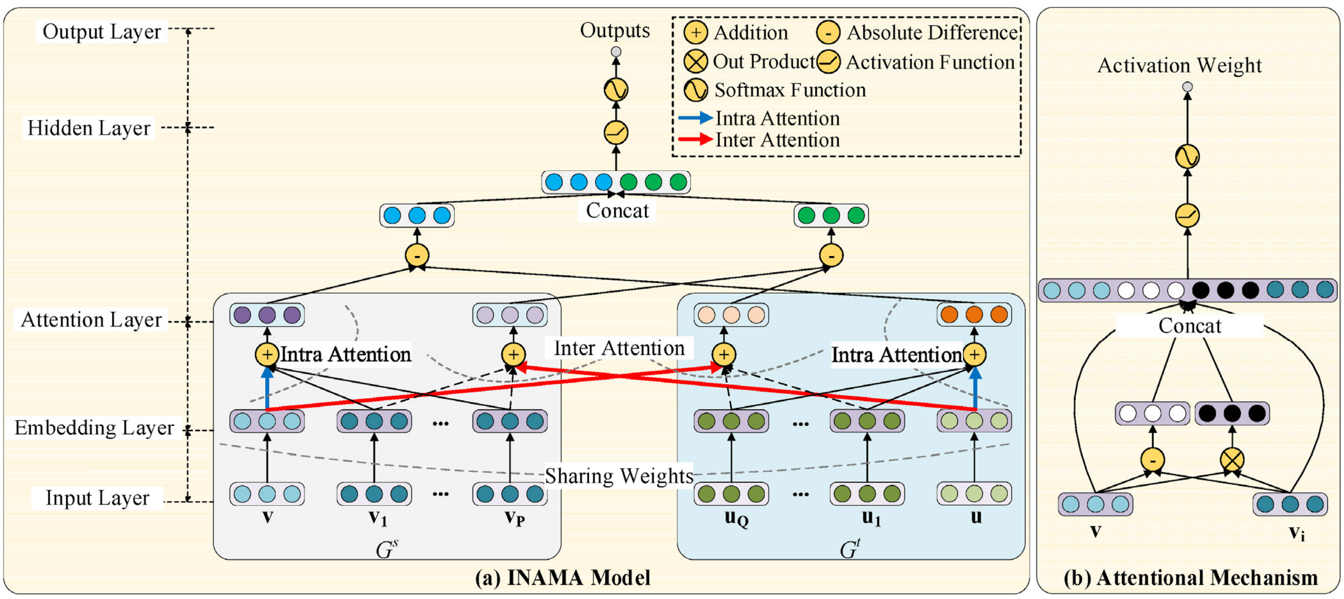


Figure 3. The framework of INAMA. (a) represents the main model, where blue and red lines are *w.r.t* the intra and inter attentions. (b) details the attentional mechanism, where the example refers to the intra attention of v

Next, those embeddings are input into the attention layer. As shown in Figure 3(a), the interactive attentional model includes intra and inter attentional mechanisms. To better understand it, we show the detailed computations of intra and inter attentions for *v*. According to Figure 3(b), the intra attention coefficient of *i-th* matched neighbor v_i can be formulated as follows:

$$c_{v_i} = a^T[h_v, h_{v_i}, \left|h_v - h_{v_i}\right|, h_v \otimes h_{v_i}], \quad \textbf{(3)}$$

where $a^T \in \mathbb{R}^{4d}$ denotes the weighted vector, [,] denotes combinations, $\left|h_v - h_{v_i}\right|$ and $h_v \otimes h_{v_i}$ are *w.r.t* the operations of absolute difference and out product. Similarly, the inter attention coefficient of *j-th* matched neighbor u_j can be formulated as follows:

$$c_{u_j} = a^T[h_v, h_{u_j}, \left|h_v - h_{u_j}\right|, h_v \otimes h_{u_j}] \quad \textbf{(4)}$$

Then, we normalize the coefficients with the *softmax* function. By doing so, the *i-th* intra attention coefficient and the *j-th* inter attention coefficient can be formulated as Eq. 5 and Eq. 6.

$$w_{v_i} = \frac{\exp(\text{LeakyReLU}(c_{v_i}))}{\sum_{k=1}^{P}\exp(\text{LeakyReLU}(c_{v_k}))}, \quad \textbf{(5)}$$

$$w_{u_j} = \frac{\exp(\text{LeakyReLU}(c_{u_j}))}{\sum_{k=1}^{Q}\exp(\text{LeakyReLU}(c_{u_k}))}, \quad \textbf{(6)}$$

where *exp* denotes expectation and *LeakyReLU* is adopted as the activation function. Finally, a sum pooling manner is adopted to compute the results of intra and inter attentions. It can be formulated as Eq. 7 and Eq. 8.

$$h_v^{'} = \sum_{i=1}^{P} w_{v_i} h_{v_i}, \quad \textbf{(7)}$$

$$h_v^{''} = \sum_{j=1}^{Q} w_{u_j} h_{u_j}, \quad \textbf{(8)}$$

where $h_v^{'}$ and $h_v^{''}$ are *w.r.t* the results of intra and inter attentions for *v*. Similarly, we can compute the results of intra and inter attentions for *u* as $h_u^{'}$ and $h_u^{''}$.

In hidden layer, we compute absolute differences for the candidate pair according to the attention manner. After that, we combine the results and treat it as the input for output layer. Here, a fully connected network is employed to generate predictions. The process can be formulated as follows:

$$\hat{y} = f\left([\left|h_v^{'} - h_u^{'}\right|, \left|h_v^{''} - h_u^{''}\right|]\right), \quad \textbf{(9)}$$

where f is the mapping function within a fully connected network. Finally, the cross-entropy loss function is adopted in the training phase. To be specific, given *N* training pairs and their labels, the loss function can be formulated as Eq. 10.

$$L = \frac{1}{N}\sum_{i=1}^{N} CrossEntropy(\hat{y}_i, y_i), \quad \textbf{(10)}$$

where $\hat{y}_i$ and y_i are *w.r.t* the predicted result and label of *i-th* training pair.

4 Experiments

To validate INAMA, we first show the effectiveness of it through node alignment experiments. Then, statistical tests are adopted to determine whether there're significant differences between our method and other approaches. Finally, we conduct ablation studies to show the effectiveness of each component in our model.

4.1 Experimental Setup

In this part, we present the details of datasets, baselines, the evaluation metric and implementations.

4.1.1 Datasets

In this paper, we conduct our experiments on six datasets, where three of them are SNA datasets and the other are academic datasets. The three SNA datasets are obtained from [18], namely Douban Online-Offline, Flickr-Lastfm and Flickr-Myspace. To be specific, user locations are treated as node attributes in the first dataset. User genders, including 'male', 'female' and 'unknown', compose node attributes for the other two datasets. In addition, we extract academic networks by chronological orders from DBLP, and construct the topologies around *Yoshua Begio* with no more than four-hops. To be specific, years 2016~2018 are adopted and names of conferences (journals) are treated as attributes. The authors' identities in DBLP form the alignment labels. Because node attributes are all discrete features, we represent the node attributes with the one-hot encoding manner. The detailed descriptions of datasets are shown in Table 1, where *#Link* denotes connections. *#Anchor Link* denotes the aligned pairs.

4.1.2 Baselines

We compare our method with five baselines and categorize them into three types: (1) Attribute-based methods, including KNN, SVM and ULink; (2) Topology-based methods, i.e., IONE; (3) Methods of leveraging both node attributes and topologies, namely MEgo2Vec.

- KNN: K-Nearest-Neighbor (KNN) is a nonparametric baseline. It ranks the node attribute similarities between two networks and generates *k* nearest nodes in the target network as matched candidates.

Table 1. Descriptions of datasets

Datasets	Source Network		Target Network		*#Attribute*	*#Anchor Link*
	#Node	*#Link*	*#Node*	*#Link*		
Douban Online-Offline	1118	3022	3906	16328	187	1118
Flickr-Lastfm	12974	32298	15436	32638	3	452
Flickr-Myspace	6714	14666	10733	21767	3	267
DBLP 17-16	9455	27721	11509	33858	2059	1823
DBLP 18-16	5562	15966	11509	33858	1831	1028
DBLP 18-17	5562	15966	9455	27721	1833	1156

- SVM: Support Vector Machine is a supervised binary classifier. We combine attributes of node pairs to form unified feature vectors, and train a SVM classifier based on the training pairs.
- IONE [10]: The method learns network embeddings with input/output context vector representations, and utilizes labeled and potential aligned pairs to propagate the context information across networks.
- ULink [9]: The method models node attributes in a latent space. It aims to minimize the distances of positive pairs and maximize the distances of negative pairs.
- MEgo2Vec [14]: It encodes node pairs' ego networks to address the issue. Attentional mechanisms are employed to distinguish influences of diverse neighbors in local networks. In particular, we remove the character-level CNN layers for user attributes.

Next, we summarize methods involved in this paper in Table 2. According to Table 2, INAMA is the only embedding model with low complexity, which can leverage both topologies and node attributes.

Table 2. A summary of methods involved in this paper

Method	Embedding	Topology	Attribute	Complexity
KNN			✓	Low
SVM			✓	Low
Ulink			✓	Low
IONE	✓	✓		High
MEgo2Vec	✓	✓	✓	High
INAMA	✓	✓	✓	Low

4.1.3 Evaluation Metric

Following [9], we validate all competitors by *Hit-precision* of the top-k candidates. The computation of *Hit-precision* for each test pair is as follows:

$$h(x) = \frac{k - (hit(x) - 1)}{k}, \tag{11}$$

where *hit(x)* represents the position of the matched node x in the top-k candidates. Then, the average *Hit-precision* score on N test pairs can be computed as follows:

$$Hit - precision = \frac{1}{N}\sum_{i=1}^{N} h(x_i) \tag{12}$$

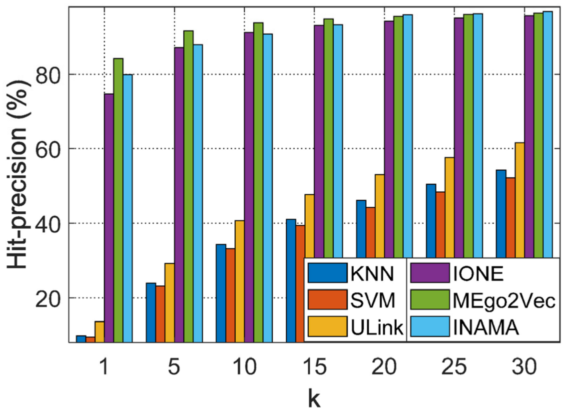
In our experiments, we select k from {1, 5, 10, 15, 20, 25, 30}, where $k = 1$ represents accuracy.

4.1.4 Implementation Details

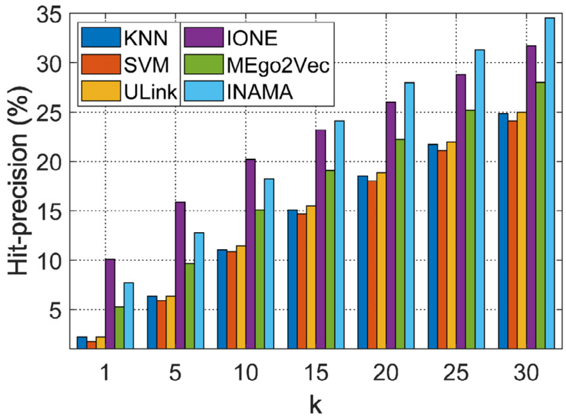
To avoid random biases, we repeat each experiment five times and report the average performance. The aligned pairs are divided into 5 folds each time, where 4 folds construct the training set and 1 fold constructs the test set. In the training phase, for each aligned pair (v,u), we generate ten negative samples $\tilde{v}$ and $\tilde{u}$, and replace v and u to obtain the negative training pairs, i.e., $(\tilde{v},u)$ and $(v,\tilde{u})$. In experiments, we train each method based on positive and negative pairs. For SVM and ULink, we select coefficient C via validation on the training data. We set the negative sampling number as 5 for network embedding in IONE. For a fair comparison, embedding sizes are set as 50 for all embedding models. In particular, we set the learning rate for INAMA as 0.001 and the training batch size as 500.

4.2 Node Alignment Experiments

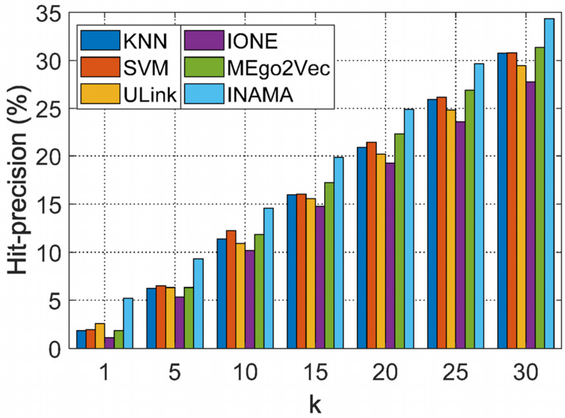
Figure 4 presents the node alignment performances. According to Figure 4, we can make the following conclusions: (1) With increasing the value of k, our model consistently delivers the best on Flickr-Myspace and three academic datasets. In addition, it also shows superiorities on another two SNA datasets when k = 20, 25, 30. Therefore, the results validate the effectiveness of our model; (2) MEgo2Vec and INAMA often perform better than the other baselines. It indicates that both node attributes and topologies contribute to node alignment; (3) Attribute-based methods, i.e., KNN, SVM and ULink, perform not well. It verifies that only utilizing node attributes cannot provide a high confidence for node alignment. Thus, to tackle the issue, we need to incorporate the topology structures; (4) The performances of INAMA are usually better than MEgo2Vec and IONE, which show both effectiveness and reasonability of utilizing matched neighbors instead of original topologies. In addition, because of leveraging both topologies and node attributes, INAMA and MEgo2Vec deliver better performances than IONE on academic datasets with rich features; (5) With increasing k value, there are consistent improvements for all methods. The reason is that matched nodes are more likely to be hit with increasing k value; (6) For our method, when $k = 1$, the performances on Flickr-Lastfm and Flickr-Myspace are much worse and the performance on Douban Online-Offline achieves quite a promising result. The reason is that the topologies of the two SNA datasets are with large scales, where the aligned pairs are with small scales. On the opposite hand, the aligned pairs and attributes of Douban Online-Offline are much larger.



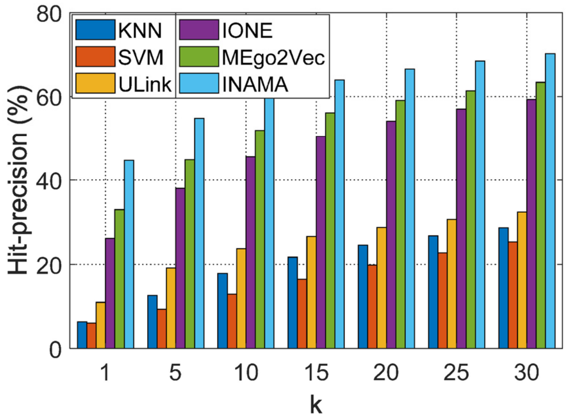
(a) Performance on Douban Online-Offline



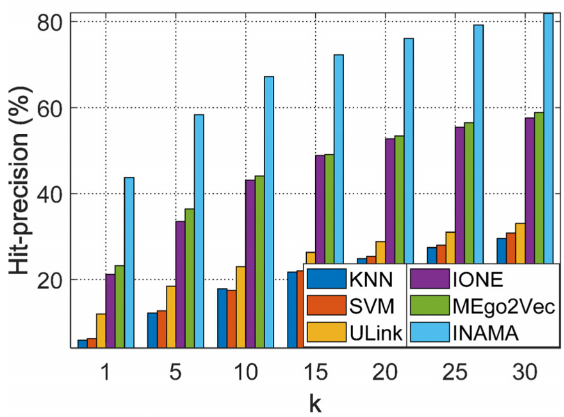
(b) Performance on Flickr-Lastfm



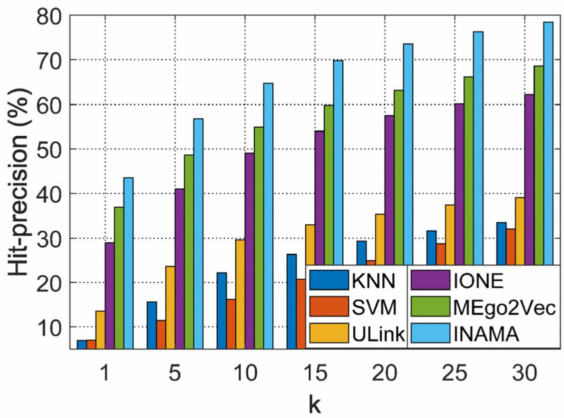
(c) Performance on Flickr-Myspace



(d) Performance on DBLP 17-16



(e) Performance on DBLP 18-16



(f) Performance on DBLP 18-17

Figure 4. Node alignment performance (%)

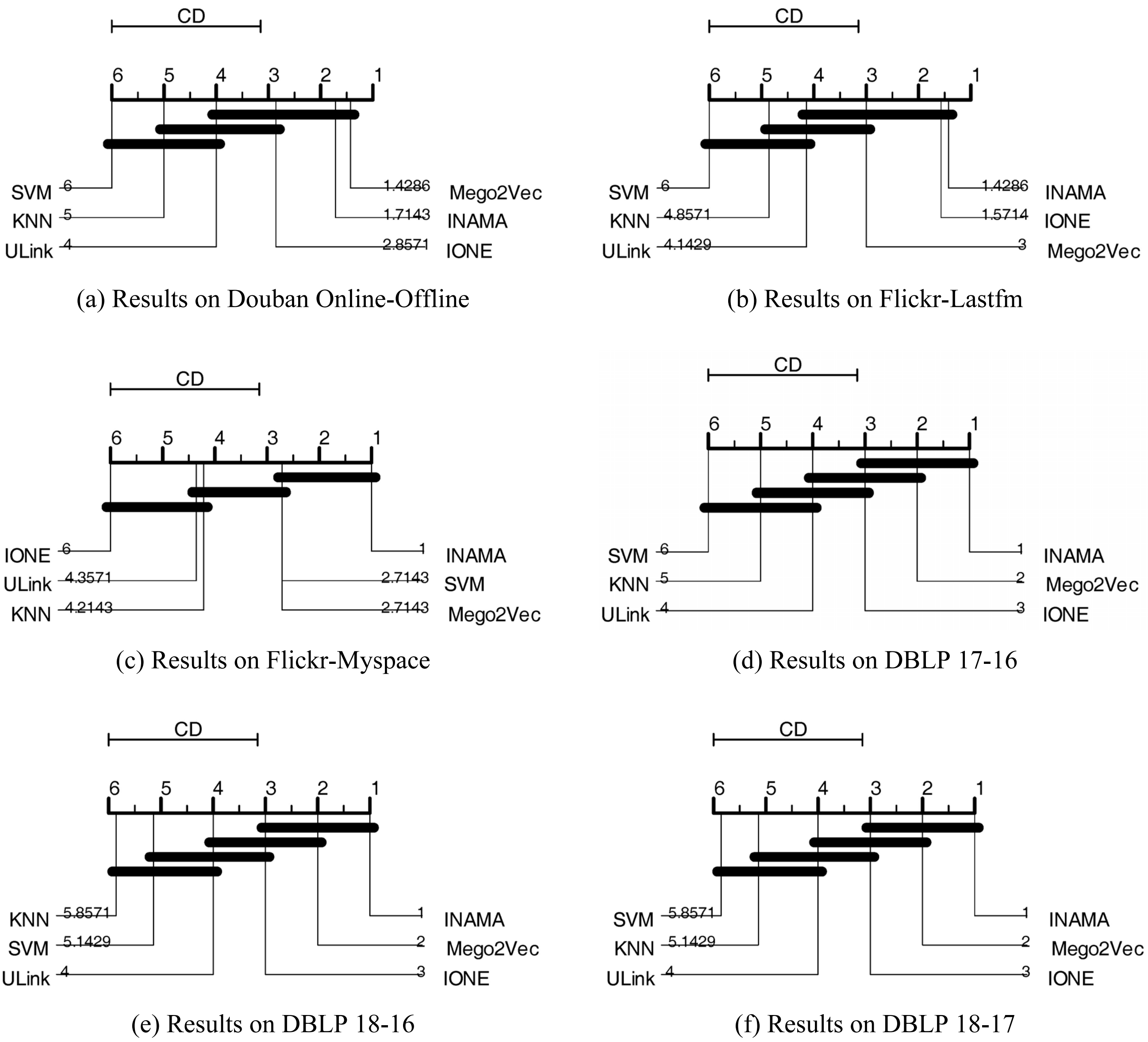
4.3 Statistical Experiments

To determine whether the performances of node alignment exist statistical differences, we first employ Friedman Test [16] to make detections. If there existed differences, the post-hoc Nemenyi Test [17] would be adopted to clear up the differences. For the Friedman Test, we treat the number of k value as blocks and the number of involved methods as treatments. Thus, numbers of blocks and treatments are *w.r.t* five and six. Table 3 shows the Friedman Test results with significant hypothesis level $\alpha = 0.05$, where p value less than α means rejecting the hypothesis and there exist significant differences. According to Table 3, significant differences exist on all datasets and the post-hoc Nemenyi Test should be conducted.

Before conducting the Nemenyi Test, we briefly introduce the experimental steps. It firstly computes the average rank for each method based on node alignment results with different k settings. According to [17], the small (large) rank represents the better (worse) performance. Then, it calculates the critical distance (CD), which depends on numbers of blocks and treatments with a given critical value (0.05 is used here). Finally, the rank difference for arbitrary two methods is larger than CD, indicating that they have a statistical difference. Because of the same numbers of treatments and blocks, the CD values on all datasets are equal to 2.85. Figure 5 shows the Nemenyi Test results, where the top line represents CD and the lowest ranks are at the right-most side of the axis.

Table 3. Friedman Test results

Dataset	p value	Hypothesis
Douban Online-Offline	3.3024×10^{-6}	×
Flickr-Lastfm	2.6017×10^{-6}	×
Flickr-Myspace	1.3435×10^{-6}	×
DBLP 17-16	1.5047×10^{-6}	×
DBLP 18-16	1.8842×10^{-6}	×
DBLP 18-17	1.8842×10^{-6}	×



(a) Results on Douban Online-Offline

(b) Results on Flickr-Lastfm

(c) Results on Flickr-Myspace

(d) Results on DBLP 17-16

(e) Results on DBLP 18-16

(f) Results on DBLP 18-17

Figure 5. Nemenyi Test results

Specifically, methods do not differ significantly with a bold line. Therefore, we can make the following conclusions: (1) INAMA delivers the best on most datasets except Douban Online-Offline; (2) INAMA significantly performs better than SVM and KNN in all cases, and it shows statistical superiorities than ULink on academic datasets and Flickr-Myspace; (3) The ranks of MEgo2Vec take up high orders in most cases. It is because the method incorporates both topologies and node attributes to learn the node alignment task-oriented embeddings; (4) The attribute-based methods, i.e., KNN, SVM and ULink, often take up low orders. It again verifies that only using node attributes couldn't give sufficient clues for node alignment.

4.4 Ablation Experiments

According to Figure 3, INAMA is affected by three aspects, i.e., node inputs, neighbors and attentions. In other words, node attributes, matched neighbors, intra and inter attentions all contribute to our model. To validate the effectiveness and reasonability of each aspect, we conduct ablation experiments. To validate the effectiveness of node attributes, we encode node ids in one-hot form to replace the original ones. The variant model is named as '*w/o attr*'. For matched neighbors, intra and inter attentional mechanisms, we remove respective neural networks to validate the effectiveness of topologies and interactive attentions, where the corresponding variant models are named as '*w/o MN*', '*w/o intra*' and '*w/o inter*'. Figure 6 shows the ablation study results, where '*Original*' represents our method. Therefore, we can make the following conclusions: (1) Compared to the performances of '*w/o attr*' and '*Original*', it shows existing significant differences on the datasets with rich inputs. That is to say our model satisfies the datasets with rich inputs; (2) Compared to the performances of '*w/o MN*' and '*Original*', it again validates the effectiveness of defining matched neighbors and also reveals the reasonability; (3) Observing the results of '*w/o intra*', '*w/o inter*' and '*Original*', we can see that our model is slightly better than the other two variants in most cases. Thus, it validates both intra and inter attentions. To sum up, the ablation study validates the effectiveness of each component.

5 Related Work

In earlier works, comparing names to solve node alignment problems was widely studied. For instance, Zafarani et al. [6] proposed a node alignment method by adding or removing prefixes or postfixes of names. Soon afterwards, they incorporated the habits of names to make comprehensive study for node alignment problem [7]. Kong et al. [8] tried to align nodes by comparing the cosine similarities of the TF-IDF textual features of names. In [9], Mu et al. tackled the issue by mapping users in a latent space with a metric learning approach. Because of heterogeneous node attributes, these works do not well address the node alignment problem.

In terms of aforementioned analysis, topologies also contribute to node alignment. Therefore, many topology-based attempts are proposed. For example, Zhou et al. [19] computed similarities of shared neighbors with Adamic-Adar metric. However, the method cannot well satisfy the datasets with sparse aligned pairs. With the development of network embedding, embedding nodes into deep latent space to align nodes is also well studied. For instance, IONE [10] and PALE [11] are the two representative methods, where the network embedding technique is adopted to align pairs. Although the above methods leverage topologies, they all ignore node attributes, which also contribute to the task.

Recently, incorporating both node attributes and topologies to tackle node alignment problem has become a hotspot. For example, there exist some unsupervised methods by decomposing matrixes of the two aspects, such as [18]. In [20], an unsupervised co-training model is proposed, which integrates both node attributes and topologies for node alignment. Zhang et al. [13] tackled the problem by a supervised manner to utilizing the two aspects and inferring labels. As an advanced method, MEgo2Vec [14] designs an ego network for each pair, and incorporates both structural consistencies and node attributes to learn task-oriented node embeddings. Although the above methods leverage both aspects, they cannot capture the interactive neighbor influences, where our method addresses it nicely.

6 Conclusion

With the intensive study of SNA, node alignment becomes a hot topic. Previous studies have mostly failed to adequately address the issue. In this paper, we present a novel interactive attentional model, which leverages both topology structures and node attributes for node alignment. On one hand, our model leverages topology structure information efficiently based on the defined matched neighbors. On the other hand, intra and inter attentional mechanisms are employed to distinguish the neighbor influences from local and across networks, respectively. The performances of several experiments consistently show the superiority of our model against the state-of-the art methods.

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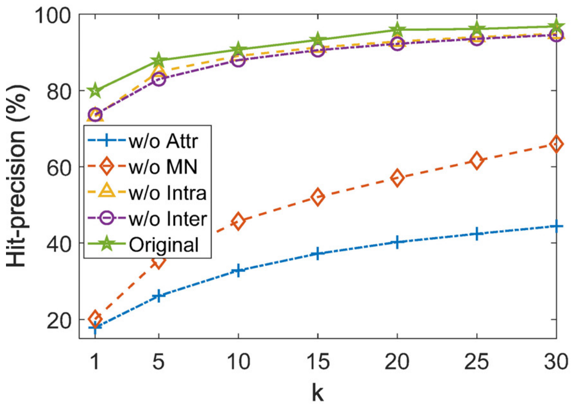
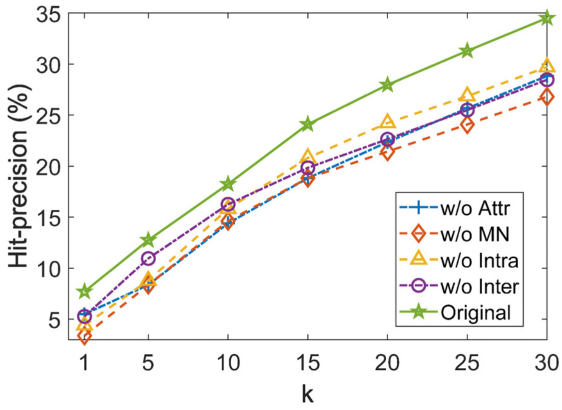
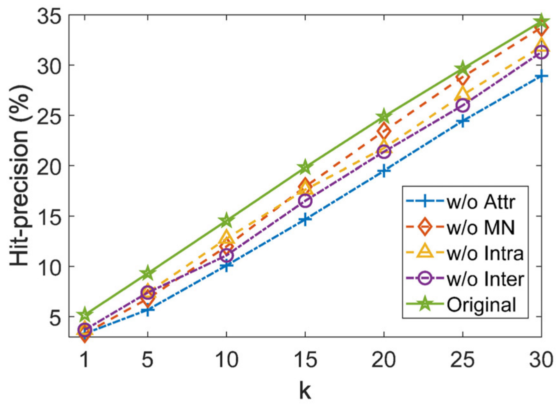


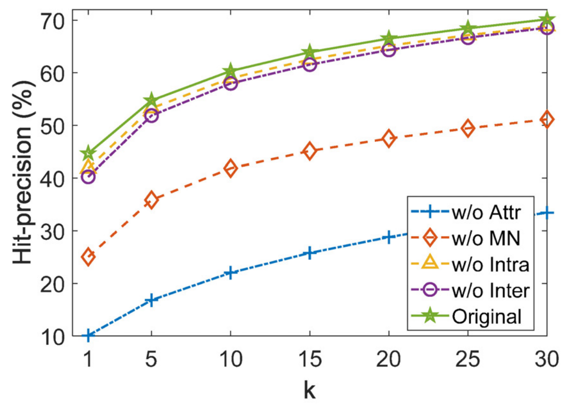
(a) Results on Douban Online-Offline



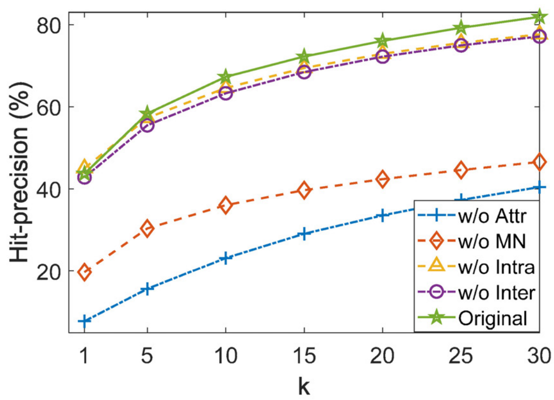
(b) Results on Flickr-Lastfm



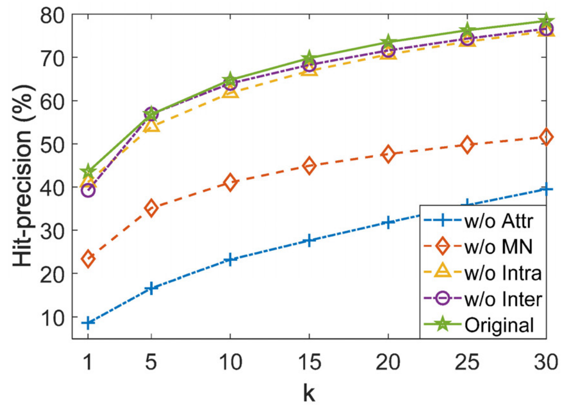
(c) Results on Flickr-Myspace



(d) Results on DBLP 17-16



(e) Results on DBLP 18-16



(f) Results on DBLP 18-17

Figure 6. Ablation study results (%)

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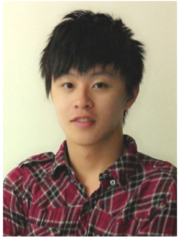

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