Unsupervised Meta-path Reduction on Heterogeneous Information Networks

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Abstract
Heterogeneous Information Network (HIN) has attracted much attention due to its wide applicability in a variety of data mining tasks, especially for tasks with multi-typed objects. A potentially large number of meta-paths can be extracted from the heterogeneous networks, providing abundant semantic knowledge. However, though a variety of meta-paths can be defined, too many meta-paths are redundant. Reduction on the number of meta-paths can enhance the effectiveness since some redundant meta-paths provide inferential linkage to the task. Moreover, the reduced meta-paths can reflect the characteristic of the heterogeneous network. Previous endeavors try to reduce the number of meta-paths under guidance of supervision information. Nevertheless, supervised information is expensive and may not always be available. In this paper, we propose a novel algorithm, SPMR (Semantic Preserving Meta-path Reduction), to reduce a set of pre-defined meta-paths in an unsupervised setting. The proposed method is able to evaluate a set of meta-paths to maximally preserve the semantics of original meta-paths after reduction. Experimental results show that SPMR can select a succinct subset of meta-paths which can achieve comparable or even better performance with fewer meta-paths.

Introduction
Information networks, such as friendship networks and gene networks, have been widely studied in various data mining tasks, such as community detection (Leskovec, Lang, and Mahoney 2010) and collective classification (Lu and Getoor 2003). Traditional information networks usually assume the nodes are of the same type, and such networks are usually referred to as homogeneous networks. However, in the era of big data, different types of real-world objects from various domains are often inter-connected. For example, in bibliographic network (e.g., DBLP\textsuperscript{[1]}, author, paper, term and venue constitute a multi-typed network in which different types of relationship (Figure 1a) exist among nodes (e.g., author 'wrote' paper, paper 'contains' term). In social media network (e.g., Twitter/BlogCatalog), objects including tweet/blog, user, hashtag/tag and term also interact with each other (Figure 1b). Heterogeneous Information Network (HIN) (Sun et al. 2012) (Sun et al. 2013) has been proposed to model such interacting multi-typed objects. Due to its versatility in modeling inter-connected objects, HIN has been employed in a wide variety of applications, including recommendation (Yu et al. 2014), classification (Kong et al. 2012) (Kong, Cao, and Yu 2013), clustering (Sun et al. 2012) and information fusion (Kong, Zhang, and Yu 2013) (Zhang, Yu, and Zhou 2014).

In order to utilize the rich information embedded in HIN, one popular way is to extract meta-paths (Sun, Yu, and Han 2009) from the heterogeneous network. Meta-path is a sequence of relations which captures the correlation among object types. Generally, there are a variety of meta-paths in a heterogeneous network. Applying all types of meta-paths at the same time may lead to low-efficiency problem. Moreover, some meta-paths may carry misleading information, known as social noise (Liu et al. 2017), which can become an interference to the tasks. According to our experiment, a small subset of meta-paths can provide sufficient information. Hence, it is desirable to reduce the number of meta-paths so that the performance could be better and the characteristic of HIN can be revealed explicitly.

In a supervised scenario, the reducing process of the number of meta-paths is relatively easy, as supervision can be used as a guidance for weighting different meta-paths. The supervision information can be user (implicit) feedback for recommendation problem (Yu et al. 2014) or class label for classification problem (Kong, Zhang, and Yu 2013). The meta-paths having higher correlation with the supervision information can be retained and the meta-paths with little correlation can be discarded.

However, supervision information is not always available and it is usually expensive to obtain. In this paper, we propose a novel approach to implement reduction on meta-paths under unsupervised setting, which is non-trivial due to the lack of guidance. This approach aims to reduce the number of a pre-defined set of meta-paths while still preserving the semantic information of the original network. Hence, the reduced subset of meta-paths can be viewed as a succinct summary of the original meta-paths. The performance of subsequent task could also be enhanced since the abandoned meta-paths may constitute the noise part of the network. Furthermore, the reduced set of meta-paths can provide human analysts better insights about the characteristic of the network.

The main contribution of this paper can be summarized as follows:
To our best knowledge, we are the first to formally study the problem of unsupervised meta-path reduction on heterogeneous information networks. We aim to select a succinct subset of meta-paths which can preserve most of the information of all the meta-paths.

- We propose a transition probability preserving approach to perform meta-path reduction, which utilizes correlation among different meta-paths.
- We conduct experiments on two real-world datasets to show that our proposed methods can perform better in terms of the clustering accuracy and the reduced set can still preserve the semantic information.

The rest of the paper is organized as follows. We present preliminary concepts in section 2 and propose the approach in section 3. Optimization one the proposed model is introduced in section 4. In section 5, experimental results are shown to compare the proposed approach with using all the meta-paths. And we review some related work in section 5 before we conclude our work in section 6.

Related Work

In this section, we review some related work on heterogeneous information network and unsupervised feature selection.

Heterogeneous Information Network

Meta-path based citation recommendation methods use the citation relationship as supervision to weight different meta-paths (Ren et al. 2014). In classification tasks, the importance of different meta-paths can be learned by the informativeness of links (Kong et al. 2012). In recommendation tasks, the implicit user feedback is used as supervision to learn the weights of meta-paths (Yu et al. 2013). For link prediction tasks, the existence of links provides guidance to learn importance for different meta-paths (Zhang, Kong, and Yu 2014). When used in information fusion such as cross-network mapping (Kong, Zhang, and Yu 2013), the importance of meta-path weights is learned under the supervision of anchor link.

In semi-supervised clustering, PathSelClus (Sun et al. 2012) requires user guidance to weight different meta-paths for clustering HIN and the HIN can be clustered in different ways based on the user input. SemiRPClus also learns the importance of meta-paths based on labeled information for performing semi-supervised clustering (Luo, Pang, and Wang 2014).

However, how to select informative meta-paths in unsupervised scenario has received little attention. Existing work on unsupervised task with meta-paths (e.g., clustering) typically use all the meta-paths generated from the network (Wang et al. 2015). The performance of such an approach might be affected by low-quality meta-paths and suffers from poor interpretability.

Unsupervised Feature Selection

In unsupervised feature selection, different heuristics have been explored for selecting features. Selecting features by their spectral property is a popular class of approaches (He, Cai, and Niyogi 2005). However, these simple heuristics can only evaluate features individually and ignore the correlation among features. Recent methods attempt to overcome this issue by evaluating the subset of features as a whole. Notably, $L_{2,1}$ norm based methods (Yang et al. 2011) (Li et al. 2012) (Qian and Zhai 2013) (Du and Shen 2015) have gained much popularity among others. The feature selection problem is performed jointly with linear subspace learning/linear regression. In such methods, the features are evaluated by their utility in the regression problem. Sparsity-inducing $L_{2,1}$ norm is employed to enforce the weights of less useful features shrink to zero. For example, Non-negative Discriminative Feature Selection (NDFS) (Li et al. 2012) performs non-negative spectral analysis and feature selection jointly. Robust Unsupervised Feature Selection (RUFS) (Qian and Zhai 2013) and Robust Spectral Feature Selection (RSFS) (Shi, Du, and Shen 2014) study feature selection robust to outlier instances by using $L_{2,1}$ norm and Huber loss, respectively. FSASL (Du and Shen 2015) employs adaptive structure learning to be more resilient to the noise in the local structure. However, these approaches can only be applied to feature vectors and is not applicable to meta-path selection.
Table 1: Examples of meta-paths derived from two datasets

| Datasets         | Examples of meta-path                                                                 |
|------------------|---------------------------------------------------------------------------------------|
| BlogCatalog      | Blog $\xrightarrow{\text{has}}$ Tag $\xrightarrow{\text{has}^{-1}}$ Blog            |
|                  | Blog $\xrightarrow{\text{written}}$ User $\xrightarrow{\text{written}^{-1}}$ Blog   |
|                  | Blog $\xrightarrow{\text{written}}$ User $\xrightarrow{\text{friend}}$ User $\xrightarrow{\text{written}^{-1}}$ Blog |
| DBLP             | Paper $\xrightarrow{\text{has}}$ Term $\xrightarrow{\text{has}^{-1}}$ Paper           |
|                  | Paper $\xrightarrow{\text{written}}$ Author $\xrightarrow{\text{written}^{-1}}$ Paper |
|                  | Paper $\xrightarrow{\text{written}}$ Author $\xrightarrow{\text{written}^{-1}}$ Paper |
|                  | $\xrightarrow{\text{has}}$ Term $\xrightarrow{\text{has}^{-1}}$ Paper               |
| Chemical Compound| Compound $\xrightarrow{\text{bind}}$ Gene $\xrightarrow{\text{PPI}}$ Gene $\xrightarrow{\text{bind}^{-1}}$ Compound |
|                  | Compound $\xrightarrow{\text{treat}}$ Disease $\xrightarrow{\text{cause}^{-1}}$ Gene $\xrightarrow{\text{bind}^{-1}}$ Compound |
|                  | Compound $\xrightarrow{\text{bind}}$ Gene $\xrightarrow{\text{has}}$ Pathway $\xrightarrow{\text{has}^{-1}}$ Gene $\xrightarrow{\text{bind}^{-1}}$ Compound |

Preliminaries

In this section, we present some preliminary concepts used in this paper.

**Definition 1 Heterogeneous Information Network** The complex side information of data instances can be represented as a Heterogeneous Information Network (HIN) $\mathcal{G} = (V,E)$. $V$ denotes the set of nodes, which includes $t$ types of entities, $V_1 = \{v_1, v_2, \ldots, v_{1n_1}\}$, $\ldots$, $V_t = \{v_{1}, v_{2}, \ldots, v_{tn_t}\}$. $E$ denotes the set of (multiple types of) links $E \subset V \times V$.

HIN models the heterogeneous relationship among interconnected objects. There are various types of real-world data that can be represented as heterogeneous information networks:

- Blog network: From a blog user network (Figure 1b), one could extract the following four types of relationships: user writes blog post, which has associated tag and term. Besides, users are connected with each other by friendship links. Other social media data, such as Twitter and Flickr, can be represented as heterogeneous network in similar manner.

- Bibliographic network (Figure 1a): there are four types of entities: author, venue, paper, term, where paper contains terms, is written by author and gets published in certain venue. Also, a paper could cite other papers.

- Bioinformatic network: HIN can also represent different entities involved in biological processes. For example, certain disease may be caused by some genes and can be cured by certain chemical compound, which could cause side effects. Such interactions between gene, pathway and chemical compound can be represented as HIN (Figure 1c).

For the type of nodes on which one want to perform machine learning task, we refer to them as target nodes in the heterogeneous information network. For example, if the goal is to cluster blog posts, the blog post nodes are the target nodes in the blog network.

To extract knowledge from HIN, a popular approach is to generate meta-paths which is defined as follows.

**Definition 2 Meta-path** A meta-path $\mathcal{P}$ of length $l$ is a sequence of relations $\mathcal{R}_i$ ($i = 1, \ldots, l$), i.e., $\mathcal{R}_1 \xrightarrow{R_1} \mathcal{R}_2 \xrightarrow{R_2} \cdots \xrightarrow{R_l} \mathcal{T}_{l+1}$, where $\mathcal{T}_i$ ($i = 1, \ldots, l + 1$) are the types of nodes. A unique sequence of nodes is referred to as a path instance of $\mathcal{P}$.

For each pair of nodes, various meta-paths can be extracted to provide information about their correlations from different perspectives. Each meta-path usually carries certain semantics between instances. For example, paper-author-paper links the papers written by the same author and paper-venue-paper connects the papers appearing in the same conference. While papers connected by either meta-path are likely to be in the same research area, the former meta-path tends to contain finer grained information. Examples of meta-paths on different HINs can be found in Table 1.

A typical way of utilizing the meta-paths is to derive certain similarity/affinity measure from them. Inspired by the path-counting measure in (Sun et al. 2011), we define the following side information-based (asymmetric) affinity measure by counting the meta-path instances between the target data points.

**Definition 3 Max-normalized Meta-path Count** Given a side information network, we define the following affinity measure from the side information w.r.t meta-path $m \in M$ as follows:

$$S_{ij}^{(m)} = \frac{|\mathcal{P}(m)(i \xrightarrow{\mathcal{R}} j)|}{\max_{k \neq i}(|\mathcal{P}(m)(i \xrightarrow{\mathcal{R}} k)|)}$$  \hspace{1cm} (1)

where $|\mathcal{P}(m)(i \xrightarrow{\mathcal{R}} j)|$ denotes the number of path instances with type $m$ between data instances $i$ and $j$, and $|\mathcal{P}(m)(i \xrightarrow{\mathcal{R}} j)|$ denotes the number of out-going path instances of type $m$ from instance $i$. This metric is similar to PathSim (Sun et al. 2011) in spirit, but PathSim is only applicable for symmetric meta-paths. And we use max-normalization to better preserve the semantic information from our experiment.
Since each meta-path reveals partial information to the correlation between two nodes, combining them together into an aggregated measure provides a more comprehensive view of the correlation. Assuming there are $M$ meta-paths of interest w.r.t. certain type of target node: $\mathbb{P}^{(1)}$, $\mathbb{P}^{(2)}$, ..., $\mathbb{P}^{(M)}$, we can define the following aggregated affinity.

**Definition 4 Aggregated Meta-path Affinity** For target type $i$ in a heterogeneous information network, we can aggregate the normalized meta-path count of all the meta-paths of interest, into an aggregated meta-path affinity as follows:

$$ A_{ij} = \sum_{m=1}^{M} s_{ij}^{(m)} $$  

where $i, j \in \{1, 2, \ldots, n_t\}$.

If two nodes are connected by many meta-paths, it indicates they are highly correlated the and the aggregated affinity between them tends to be large.

It should be noted that some meta-paths might be of lower-quality than others. Also, different meta-paths could contain overlapping or redundant information. For instance, one could derive the following meta-paths related to social network with different levels of proximity: Blog-User-User-Blog, Blog-User-User-User-Blog, Blog-User-User-User-User-Blog and so on. We denote them as $BU^2B$, $BU^3B$ and $BU^4B$, respectively. $BU^2B$ captures the first-order proximity between users, which represents the correlation between the blogs written by users who are friends. When the network is sparse, it is desirable to incorporate the second order proximity among users (i.e., friends of friends $BU^3B$). One could extract meta-path with even higher length, such as $BU^4B$ and $BU^5B$. All these meta-paths attempt to exploit the homophily effect of social network and hence carry similar semantic. So, there exists certain redundancy among these meta-paths and it might not be necessary to use all of them. Besides, the utility of these meta-paths is not the same. It is helpful to reduce the number of meta-paths to a succinct subset of meta-paths, which could potentially improve the subsequent machine learning tasks and enhance interpret ability. Therefore, we define the following meta-path reduction problem.

**Definition 5 Meta-path Reduction Problem** Our goal is to reduce the $M$ meta-paths set to a $D$ meta-paths subset, where $D < M$. We use $w \in \{0, 1\}^M (i = 1, \ldots, M)$ as an indicator vector: $w_m = 1$ indicates the $m$-th meta-path is selected and $w_m = 0$ otherwise.

As supervision information is not always available, (e.g., in clustering analysis), we aim to propose an effective approach, which generate a reduced subset of $D$ meta-paths that can preserve most of information of all the meta-paths.

**Semantic Preserving Meta-path Reduction**

In this section, we present in detail our approach for unsupervised meta-path reduction.

**Formulations** Suppose there are $n$ target nodes $v_1, v_2, \ldots, v_n$. First, we can utilize the meta-path based affinity to define transition probability between the network nodes. Let us denote the transition probability from $v_i$ to $v_j$ ($j \neq i$) as $p_{ij}$ and assume $p_{ij}$ depends on their aggregated affinity $A_{ij}$. Then we can use the softmax function to define this probability.

**Definition 6 Meta-path based Transition Probability** The following transition probability can be derived from the meta-path based affinity:

$$ p_{ij} = \frac{\exp(A_{ij})}{\sum_{k \neq i} \exp(A_{ik})} $$

where $\sum_{j=1}^{n} p_{ij} = 1$.

The larger the affinity $A_{ij}$, the larger transition probability $p_{ij}$. We also define self-transition probability $p_{ii} = 0 (\forall i = 1, \ldots, n)$ for convenience.

After meta-path selection, we can still define the transition probability in a similar manner. Let us denote the aggregated affinity on the selected meta-paths as $a_{ij} = \mathbf{w}^T \cdot s_{ij}$, where $\mathbf{w}$ is a column vector as we defined in Definition 5 and $s_{ij}$ is a column vector as $(s_{ij}^{(1)}, s_{ij}^{(2)}, \ldots, s_{ij}^{(M)})^T$. The transition probability from $v_i$ to $v_j$ after meta-path selection is $q_{ij}$:

$$ q_{ij} = \frac{\exp(a_{ij})}{\sum_{k \neq i} \exp(a_{ik})} $$

Note that $q_{ij}$ (or $p_{ij}$) is not only determined by $a_{ij}$ (or $A_{ij}$), but also affected by $a_{ik}$ (or $A_{ik}$, $k = 1, \ldots, j-1, j+1, \ldots, n$) via the normalization term. Therefore, $q_{ij}$ (or $p_{ij}$) is influenced by the relative value of $a_{ij}$ (or $A_{ij}$) compared with other $a_{ik}$ (or $A_{ik}$).

The transition probability captures the structural information among target nodes, which is also the semantics revealed by meta-paths. To preserve the semantics, we try to make two distributions $\mathbf{q}_i = [q_{i1}, \ldots, q_{in}]^T$ and $\mathbf{p}_i = [p_{i1}, \ldots, p_{in}]^T$ close by minimizing their KL divergence for each $\mathbf{x}_i$.

$$ KL(|\mathbf{q}_i|\|\mathbf{p}_i|) = \sum_{j \neq i} p_{ij} \log \frac{p_{ij}}{q_{ij}} $$

The impact of meta-paths should be measured on all pairs of target nodes. So we retain the set of $d$ meta-path which can minimize the sum of KL divergence between $\mathbf{p}_i$ and $\mathbf{q}_i$ on all the data points.

$$ \min_{w} \sum_{i=1}^{n} \sum_{j \neq i} p_{ij} \log \frac{p_{ij}}{q_{ij}} $$

s.t. $\sum_{i=1}^{M} w_{im} = d$

$\sum_{m=1}^{M} w_{im} \in \{0, 1\}, \forall m = 1, \ldots, M$

The goal is that, for nodes densely connected by meta-path instances, we still want them to have large transition probability after meta-path reduction so that the semantics can be preserved. For node pairs with low affinity (i.e., it indicates low correlation), it is desirable to keep them loosely
connected with reduced subset of meta-paths. So, by minimizing KL-divergence between \( p_i \) and \( q_i \) for \( i = 1, \ldots, n \), we get a reduced subset of meta-paths, which is indicated by the vector \( w \), that lets densely connected nodes still easier transition to each other than loosely connected nodes. Thus, the semantic information can be maximally preserved.

### Optimization

#### Relaxation

The formulation in Eq. (6) is a ‘0/1’ integer programming problem. When the total number of meta-paths is small, one can simply enumerate all combinations with size \( D \) and use the combination that leads to smallest objective function, if he/she intends to generate a subset of \( D \) meta-paths. However, when the number of meta-paths is large, such brute force approach is time-consuming to optimize. To make the optimization more efficient, we relax the ‘0/1’ constraint on \( w_m (\forall m = 1, \ldots, M) \) to real values in the range of \([0,1]\).

Also, we use Lagrangian multiplier re-write the summation constraint \( \sum_{i=1}^{M} w_m = D \)

\[
\min_w \sum_{i=1}^{n} \sum_{j \neq i} p_{ij} \log \frac{p_{ij}}{q_{ij}} + \lambda \|w\|_1
\]

\[
s.t. \ 0 \leq w_m \leq 1, \forall m = 1, \ldots, M
\]

where \( \| \cdot \|_1 \) is the \( L_1 \) norm and \( \lambda \) is the parameter to control the \( L_1 \) regularization. Note that \( |w_m| = w_m \) since \( w_i (\forall t = 1, \ldots, D) \) is always non-negative.

Now we derive the gradient update formula for SPMR. We denote \( \exp(a_{ij}) \) as \( E_{ij} \) and the normalization term \( \sum_{k \neq i} \exp(a_{ik}) \) as \( Z_i \). So \( q_{ij} \) can be denoted as \( E_{ij}/Z_i \).

We denote \( KL(p_i||q_i) = \sum_{j \neq i} p_{ij} \log \frac{p_{ij}}{q_{ij}} \) as \( L_i \). The gradient of \( L_i \) w.r.t \( s_{ij} \) can be decomposed into two terms,

\[
\frac{\partial L_i}{\partial s_{ij}} = -\frac{\partial}{\partial s_{ij}} (p_{ij} \log q_{ij}) - \sum_{k \neq j} \frac{\partial}{\partial s_{ij}} (p_{ik} \log q_{ik}).
\]

Now we derive the gradients on these two parts,

\[
\frac{\partial}{\partial s_{ij}} (p_{ij} \log q_{ij}) = \frac{p_{ij}}{q_{ij}} \frac{\partial q_{ij}}{\partial E_{ij}} \frac{\partial E_{ij}}{\partial s_{ij}}
\]

\[
= \frac{p_{ij}}{q_{ij}} \frac{Z_i - E_{ij}}{Z_i^2} \frac{\partial E_{ij}}{\partial s_{ij}}
\]

\[
= \frac{p_{ij}}{Z_i} \left( \frac{1}{A_{ij}} \right) Z_i \frac{\partial E_{ij}}{\partial s_{ij}}
\]

\[
= \frac{p_{ij}}{E_{ij}} \left( \frac{1}{A_{ij}} \right) Z_i \frac{\partial E_{ij}}{\partial s_{ij}}
\]

\[
= \frac{p_{ij}}{E_{ij}} \left( \frac{1}{A_{ij}} \right) Z_i \frac{\partial E_{ij}}{\partial s_{ij}} - p_{ij} \frac{1}{Z_i} \frac{\partial E_{ij}}{\partial s_{ij}}
\]

\[
\sum_{k \neq j} \frac{\partial}{\partial s_{ij}} (p_{ik} \log q_{ik}) = \sum_{k \neq j} p_{ik}/q_{ik} \frac{\partial q_{ik}}{\partial E_{ij}} \frac{\partial E_{ij}}{\partial a_{ij}}
\]

\[
= \sum_{k \neq j} -p_{ik}/q_{ik} \frac{E_{ik}/Z_i^2}{A_{ij}} \frac{\partial E_{ij}}{\partial a_{ij}}
\]

\[
= \sum_{k \neq j} -p_{ik}/Z_i \frac{\partial E_{ij}}{\partial a_{ij}}
\]

By combining them together, it is able to get the following gradient by observing \( p_{ij} + \sum_{k \neq j} p_{ik} = 1 \),

\[
\frac{\partial L_i}{\partial a_{ij}} = -p_{ij} \frac{1}{E_{ij}} \frac{\partial E_{ij}}{\partial a_{ij}} + p_{ij} \frac{1}{Z_i} \frac{\partial E_{ij}}{\partial a_{ij}}
\]

\[
+ \sum_{k \neq j} p_{ik} \frac{1}{Z_i} \frac{\partial E_{ij}}{\partial a_{ij}}
\]

\[
= -(p_{ij} \frac{1}{E_{ij}} - 1 \frac{1}{Z_i}) \frac{\partial E_{ij}}{\partial a_{ij}}
\]

\[
= -(p_{ij} - q_{ij})
\]

The gradient of loss function \( L \) w.r.t \( w_i \) is calculated as follows,

\[
\frac{\partial L}{\partial w_m} = \sum_{i=1}^{n} \sum_{j \neq i} \frac{\partial L_i}{\partial a_{ij}} \frac{\partial a_{ij}}{\partial w_m} + \lambda \frac{\partial |w_m|}{\partial w_m}
\]

\[
= -\sum_{i=1}^{n} \sum_{j \neq i} (p_{ij} - q_{ij}) s_{ij}^{m} + \lambda.
\]
Intuitively, when \( v_i \) is more likely to connect to \( v_j \) than expected (i.e., \( p_{ij} < q_{ij} \)), the reduced subset of meta-paths with large \( s_{ij}^{(m)} \) would be punished to push them away; when the transition probability from \( v_i \) to \( v_j \) is smaller than desired (i.e., \( p_{ij} > q_{ij} \)), \( w_m \) is updated to pull them closer. Thus, the semantic information can be preserved as originally. If a meta-path has little contribution in preserving the semantics, its weight tends to converge to 0 with \( L_1 \) regularization, i.e., it will be reduced.

### Projected Quasi-Newton Method

To handle the \([0, 1]\) box constraint in the optimization problem, we employ projected Quasi-Newton Method [Bertsekas, 1982]. The reason why we apply Quasi-Newton method is because for a large HIN, the dimension problem is crucial. And in each iteration, it projects \( w_m \) (\( \forall m = 1, \ldots, M \)) to the range of \([0, 1]\) after each gradient update with Eq (12)

\[
[\text{Proj}_{[0,1]}(w)]_m = \min(1, \max(0, w_m)).
\]

Since larger value of \( w_m \) indicates higher importance of meta-path, one can retain all the meta-paths with \( w_m \) close to 1 (e.g., 0.9). Also, larger \( \lambda \) would lead to weights of more meta-paths shrink towards zero and less number of meta-paths with \( w_m \) close to 1. Hence, if the goal is to select \( D \) meta-paths, he/she could choose the appropriate \( \lambda \) that makes \( \sum_{m=1}^{M} I(w_m > 0.9) = D \), where \( I \) is an indicator function such that when \( w_m > 0.9 \), its value is equal to 1. We adopt this approach to set \( \lambda \) for SPMR in the following experiments.

### Experiments

In this section, we evaluate the proposed SPMR on two real-world datasets.

### Datasets

We use the following two datasets:

- **BlogCatalog** ([Wang et al. 2010](http://dlm1.asu.edu/users/xufei/datasets. html)). A subset of blog post dataset in the following categories: {Personal Development, Investing, Fitness, Soccer, Cars}. The heterogeneous network contains users (U), blog posts (B), words (W) and tags (T) as nodes. The dataset contains around 90,000 users with social network. Blog posts are used as target nodes in the experiments.

- **DBLP**: we use the 'four area' dataset in ([Sun, Yu, and Han 2009](http://dlm1.asu.edu/users/xufei/datasets.html)) and ([Ji et al. 2010](http://dlm1.asu.edu/users/xufei/datasets.html)), which contains author, paper, term and conference in the following areas: Data Mining, Database, Information Retrieval and Artificial Intelligence. Five representative conferences are selected for each area and a total of 20 conferences are used. All the papers terms in the paper titles are used to construct the network. The original dataset contains 14376 papers (P), 14475 authors (A) and 13571 terms (T). However, only 4057 authors have ground-truth labels, we only use these authors as target nodes.

### Experimental Setting

Similar to unsupervised feature selection ([Li et al. 2012](http://dlm1.asu.edu/users/xufei/datasets.html), [Qian and Zhai 2013](http://dlm1.asu.edu/users/xufei/datasets.html), [Wei and Yu 2016](http://dlm1.asu.edu/users/xufei/datasets.html), we evaluate the quality of selected meta-paths by their clustering performance. Accuracy and Normalized Mutual Information (NMI) are used to evaluate the quality of clustering. Accuracy is defined as follows:

\[
\text{Accuracy} = \frac{1}{n} \sum_{i=1}^{n} I(c_i = \text{map}(p_i))
\]

where \( p_i \) is the clustering result of document \( i \) and \( c_i \) is its real class label, \( \text{map}(\cdot) \) maps each cluster label to a class label by using Kuhn-Munkres Algorithm ([Kuhn 1955](http://dlm1.asu.edu/users/xufei/datasets.html)).

Normalized Mutual Information (NMI) is information theory-based metric for evaluating clustering performance. Let us denote the set of clusters from the ground truth as \( C \) and cluster labels obtained from a clustering algorithm as \( C' \). Their mutual information \( MI(C, C') \) can be defined as follows:

\[
MI(C, C') = \sum_{c_i \in C, c'_j \in C'} p(c_i, c'_j) \log \frac{p(c_i, c'_j)}{p(c_i)p(c'_j)}
\]

where \( p(c_i) \) and \( p(c'_j) \) are the probabilities that a random instance from the data set belongs to \( c_i \) and \( c'_j \), respectively, and \( p(c_i, c'_j) \) is the joint probability that the instance belongs to the cluster \( c_i \) and \( c'_j \) simultaneously. In our experiments, we use the normalized mutual information as in previous work ([Li et al. 2012](http://dlm1.asu.edu/users/xufei/datasets.html)).

\[
NMI(C, C') = \frac{MI(C, C')}{\max(H(C), H(C'))}
\]

where \( H(C) \) and \( H(C') \) are the entropy of \( C \) and \( C' \). Higher value of NMI indicates better quality of clustering.

To validate the effectiveness of our proposed methods, we compare two baseline methods, which are using all meta-paths and randomly selecting (RS) \( k \) meta-paths.

### Results

The clustering results on two datasets with different numbers of selected meta-paths are shown in Table 2 and Table 3 w.r.t. accuracy and NMI respectively. We can observe that
the clustering performance can usually be improved with a reduced set of meta-paths, compared with using all meta-paths and random selecting meta-paths.

For example, on BlogCatalog dataset, for the accuracy of clustering, using 3 selected meta-paths outperforms using all paths by 42.4% and randomly selecting 3 meta-paths by 35.7%. On DBLP dataset, with respect to NMI, using 3 meta-path improves 17.0% compared with using all the meta-paths and 77.3% compared with randomly selecting 3 meta-paths. This indicates the usefulness of performing meta-path selection for unsupervised task.

Table 4 lists the selected meta-paths on BlogCatalog dataset. Selecting three meta-paths on BlogCatalog achieves the best performance, and the reduced set of meta-paths does not include word-related meta-paths. This suggests that meta-paths derived from user and tag tend to best preserve the semantic information. Additionally, from the reduction process of meta-paths, we can know the characteristics of BlogCatalog heterogeneous network. For example, the elimination of Blog - User - User - User - Blog meta-path suggests that the friends of friends relationship might not provide useful information of BlogCatalog, which can reveal the sparsity of BlogCatalog.

Table 5 lists the selected meta-paths on dblp dataset, the performance of a single meta-path Author - Paper - Author - Paper - Term - Paper - Author is similar to that of all the meta-paths, which reveals that this longest meta-path can preserve most of the semantic information. Also, the Author - Paper -Term - Paper - Term - Paper - Author is dropped as the result of redundancy. Other mate-paths can also contain this kind of semantics because the second paper must have a author, then this Author - Paper - Term - Paper - Term - Paper - Author meta-path can also be detected by Author - Paper - Term - Paper - Author meta-path.

Conclusion

From heterogeneous information networks, one could extract many meta-paths, but some meta-paths contains misleading noise or redundant information. Hence, applying reduction on the number of meta-paths, the performance of subsequent data mining tasks could be improved. Also the reduced subset of meta-paths can reveal the hidden characteristic of HIN. As supervision information is not always available, we study the problem of meta-path reduction in unsupervised setting. We propose a new method which aims to preserve the transition probability so that the semantics can be preserved. An optimization method based on projected Quasi-Newton method is proposed to solve the optimization problem. Experimental results shows the proposed SPMR can reduce the number of meta-paths in unsupervised setting, while preserving the semantic information, hence can enhance the performance of unsupervised task.
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