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學習基於異質性網路的領域感知網路表示法
Field-aware Network Embedding on Heterogeneous Networks

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國立臺灣大學碩士學位論文
口試委員會審定書

學習基於異質性網路的領域感知網路表示法

Field-aware Network Embedding on Heterogeneous Networks

本論文係陳心萍君（學號 R04944008）在國立臺灣大學資訊網路與多媒體研究所完成之碩士學位論文，於民國一百零六年六月廿九日承下列考試委員審查通過及口試及格，特此證明

口試委員：鄭卜壬（簽名）

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誌謝

感謝在我碩士生涯中幫助我的指導教授——鄭卜壬、實驗室同學、朋友以及陪伴我的家人。在這段時間裡，從老師身上，不只學習到如何切入研究問題，設計模型和實驗，並且找到適合自己的研究方向。實驗室的氣氛良好，他們是可以一起討論研究，和課業，也是一起玩的好夥伴，真心感謝能在碩士期間能有他們的陪伴。最後感謝一直陪伴我，給予我幫助的，像我第二顆 CPU 的男朋友，感謝有你。碩士畢業是我人生的一個重要的里程碑，也是開啟我下一段生活的新起點。

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中文摘要

學習網路表示法技術是目前很熱門的研究主題，此技術從複雜的網路結構學習出低維度的表示法代表節點，此表示法除了保留網路結構的關係外，讓網路中的節點能做向量的運算，對於後續的機器學習問題提供較高的基礎，像是多分類問題、預測問題和推薦問題。但是目前的學習網路表示法技術並不能很好的應用在異質性的網路中，因為異質性網路包含不同類別的節點與多種類別關係，學習後的表示法來自於不同的向量空間不能比較。基於這個原因，本篇研究將領域感知的概念應用在學習表示法技術，希望利用這種概念改善學習網路表示法技術在異質性網路中無法學習出可以比較的向量問題。本研究也應用在多個生活中的資料集，實驗證明，本研究不只能保留異質性網的關係，對於後續的機器學習問題也能有好的成果。

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Abstract

Network embedding is used for extracting the feature representations of a network and benefits many machine learning tasks, such as classification, link prediction, etc. This model embeds the interactions among the vertices into the low-dimension representations, which greatly preserve the relations of the vertices. However, to simplify the learning procedure, most previous work treats all the vertices as the same type and thus ignores the interaction type of two vertices in different fields. In the light of this, we propose a field-aware network embedding model which can separately embed the distinct kinds of the interactions into the learned representations. Our experimental results show that integrating such field-aware information indeed improves the performance of the state-of-the-art network embedding algorithm.

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Chapter 1

Introduction

Network embedding is used to learn low dimension feature representation of the vertices from a information network. The low dimension vectors are useful in many machine learning applications. For instance, in a social network, the user-user relations can be compressed into the learned representations, so it is possible to apply the group detection or people recommendations on the obtained representations. In the movie recommendation task, the embedding model can generate the low-dimension vectors based on the given user-song network, so it is able to recommend a list of movies to a specific user according what he/she likes in before. Figure 1.1 shows the diagram of network embedding usage. In short, given a relation network, the learned representations are beneficial to variant data prediction tasks.

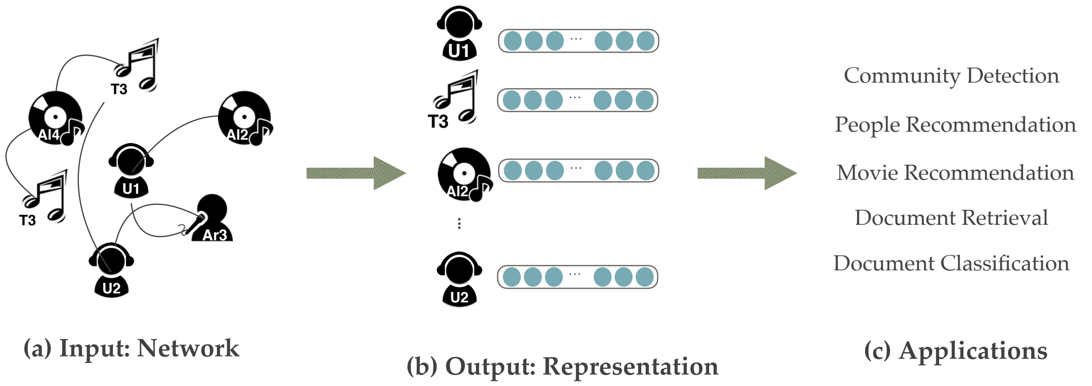

Figure 1.1: The diagram of network embedding.

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In the literature, a number of network embedding models have been proposed to learn the feature representation. Graph factorization [2, 3] uses the matrix factorization to model the interactions among the objects in a graph network so that the factorized latent vectors represents the learned representations. DeepWalk [15] exploits the random walk to sample the data relations from the network and use the skip-gram model to learn the representations. LINE [20] is the first attempt to preserve both the local and global network structure in the representations. In summary, the core of building a network embedding model is to determine which vertices are considered to be similar and which vertices are considered to be dissimilar. Given a relation network, the proposed model adopts the two criteria 1) the vertices which are connected to each other are similar to each other and 2) the vertices which share the common neighbor vertices are similar to each other.

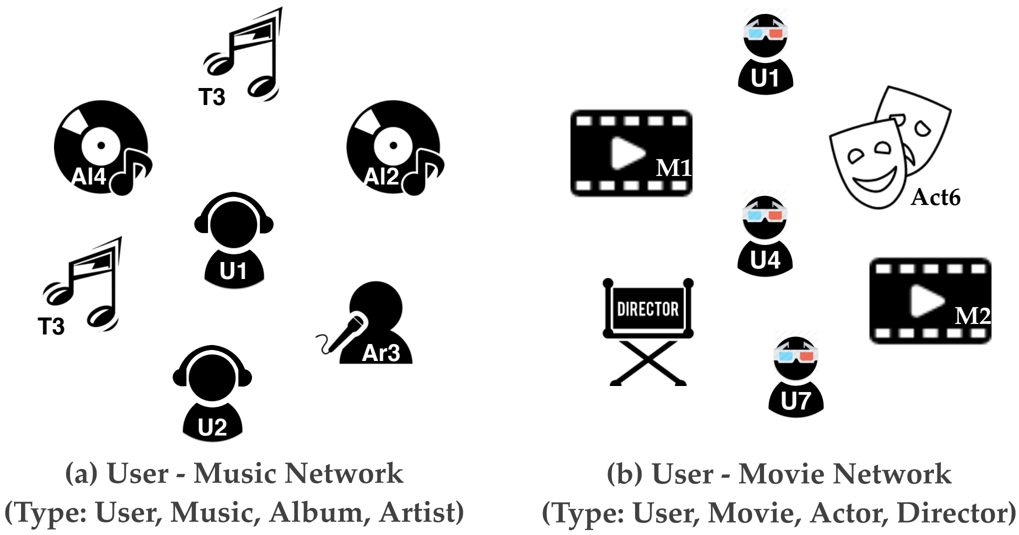

Figure 1.2: The diagram of heterogeneous network

In a real word dataset, the given network usually contains various types of vertices, which can be referred to figure 1.2. To cite examples, in a play-list recommendation problem [6], the dataset may contain the users, the tracks, the albums, the artists, ... etc, which can be referred to figure 1.2 (a). Figure 1.2 (b) is another example in a movie

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recommendation problem, the dataset[1] contains the users, the movies, the actors and the directors. The interactions in heterogeneous network are rich. For example, the user-movie relation implies the user's interest. On the other hand, the movie-actor relation is usually a binary value that represents whether an actor plays a part in the movie or not.

However, most of the existing and aforementioned network embedding models disregard such interaction differences and treat the graph network in a homogeneous style. In other words, they all simplify their modeling process by treating all the edges as one type. In addition, the weights on different types of edges in a heterogeneous network might be imbalanced. For instance, the weight of a user-movie pair might be the rating score and the movie is rated by numerous users. Since the number of users and movies are different, the weight distributions over the users and the movies are imbalanced. This problem even becomes serious in modeling a bipartite network, because the vertices are divided into two disjoint sets so the connections of one side is totally opposite to the other side.

Nevertheless, there are many works tried to tackle with heterogeneous networks. Some approaches [9] propose to re-define the edge weight between two different fields in a heterogeneous network. Some other approaches [23, 13] proposed to extract the meta-path instead of the neighbor vertices. [18, 5] use transfer learning to combine homogeneous network with imbalance heterogeneous network. In the proposed model, the unbalance issue is alleviated by the proposed field-aware training procedure, because the interactions with the variant types are trained separately.

Similar work can be found in LSHM [11] and PTE [19]. LSHM [11] uses two different projection methods to convert the heterogeneous network to one homogeneous with two kind relations. PTE [19] divides the text heterogeneous network into three sub-networks, and learned one of the relations at a time. Their idea are similar to each other, which is an attempt to convert the network structure into a special form, and tried to deal with the aforementioned imbalance learning problem. Our solution is a general solution that applies to conventional network embedding approaches.

[1] https://grouplens.org/datasets/hetrec-2011/

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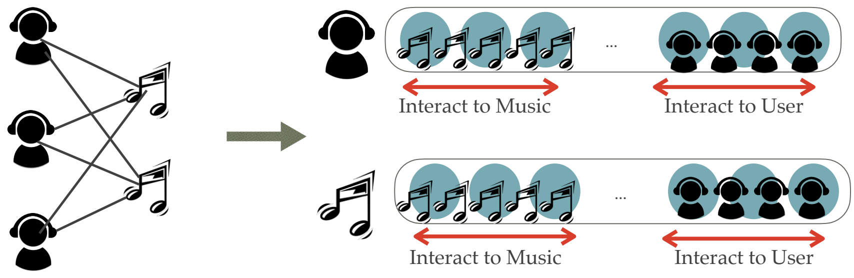

Figure 1.3: The goal of field-aware network embedding.

To address the imbalance problem, we proposed a field-aware network embedding model, which can independently learn the distinct kinds of vertex interactions based on the vertex fields. The proposed model learns multi-representation for each field, which implies the vertex position in latent space corresponding field, like the demonstration in figure 1.3. In fact, modeling the variant types interactions has been recognized as a useful method in factorization-based models [16, 12], but the presented solution is not directly applicable to the existing network embedding models. Hence, we propose the field-aware embedding providing a more suitable solutions to the network embedding models by considering the similar concepts.

Our major contributions are as follows:

- A field-aware network embedding model is proposed to embed variant types of interactions into the learned representations from a heterogeneous network.
- Due to that different interaction types are modeled separately, it alleviates the imbalance training issue.
- We conduct the experiments on three public datasets. The proposed model can outperform than general network embedding method which do not consider the interaction types.

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Chapter 2

Related Works

Our work is mainly involved with the three parts, 1) the concept of field-aware, 2) the technique of network embedding algorithms and 3) the work related to heterogeneous networks.

2.1 The idea of field-aware

FFM [12] used the field-aware concept in factorization machine, the model performs well in Click Through Rate (CTR) prediction problem. The factorization machine estimates the effect of feature conjunction by factorizing it into a product of two latent vectors. Therefore, every feature has only one latent vector to learn the latent effect with any other features. However, when it comes to 3 or more fields, the latent effect from different fields may be different. FFM tackles the problem with the idea of field-aware, makes the model learns different depending on the field of other features. In the proposed model, we use the similar concept of field-aware to deal with the incomparable problem in heterogeneous networks embedding.

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2.2 Network Embedding algorithms

Network embedding becomes popular for its efficiency and effectiveness. The learned low-dimensional vector from network structure is useful for many machine learning applications, such as link prediction, classification, ..., etc. One main reason is that the learned representations greatly keeps the vertices relations and the network structure in the given network. Moreover, these representations are vector-computable, which keeps the vertices similarity information.

In the literature, there are a number of network embedding models have been proposed to learn the feature representation. Graph factorization [2, 3] uses the matrix factorization to model the interactions among the objects in a graph network so that the factorized latent vectors represents the learned representations. GraRep [4] focus on the high-order relations and combine it with singular value decomposition (SVD) to construct multi-step learned representations. DeepWalk [15] exploits the random walk to sample the data relations from the network and use the skip-gram model to learn the representations. Node2Vec [8] learns high-order information based on the estimate the transition probability of neighborhoods. LINE [20] is the first attempt to preserve both the local and global network structure in the representations. In summary, the core of building a network embedding model is to determine which vertices are considered to be similar and which vertices are considered to be dissimilar. Given a relation network, the proposed model adopts the two criteria 1) the vertices which are connected to each other are similar to each other and 2) the vertices which share the common neighbor vertices are similar to each other.

In addition, some network embedding models try to going deep. SDNE [21] follows the same concepts in LINE and adopts a semi-supervised deep learning model. HNE [5] uses transfer learning to combine the several different networks together. However, most of these models are supervised learning algorithms. They optimize the goals depending on specific task, while our work focuses on the unsupervised learning solution to an arbitrary network.

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2.3 Heterogeneous Networks

Most of the real world datasets are heterogeneous networks, and they contain at least two different data types, such as the social network (user-content), the purchase networks(user-item), the citation networks (author-paper-conference), the language networks (document-word-label). Therefore, learning the relations in heterogeneous networks is an attracting research topic.

There also exists several researches using heterogeneous networks. [13] pre-defines some rules to capture the information in paper citation networks. [9] re-defines the weights among different types and finds out 16 relationships in online music streaming services (MSS). [14] tries to discover meta-path automatically in knowledge-based problem. These kinds of defined meta-path method [23, 17] are not only improving the performance in machine problem but also interpretable. However, such rule-based solutions require specific background/domain knowledge to enable the learning process.

Some researches [5, 18] learn only one latent vector at a time, than to project the latent vectors into the same latent space. [1] proposes a statistical model called nCRF to combine the topic model for social media (Tweets) with geographical location. Although these kinds of method provide the representations cross networks, they ignore the relation of different types during the optimization/learning steps.

[11] reconstructs the heterogeneous network into one homogeneous network. [19] divides the text heterogeneous network into three network, because the learned representations from previous network embedding algorithms are incomparable. However, the proposed method is not suitable for general case. In this paper, we proposed the general-purpose field-aware network embedding algorithm to model different relationships in heterogeneous network and provide multi-representations for each vertices.

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Chapter 3

Methodology

3.1 Problem Definition

We define a graph $G = (V, E)$, where V contains a set of vertices and E contains a set of edges. Each vertex represents an instance in the dataset and belongs to a certain field f. Each edge presents the relation between two certain vertices. In order to increase the information from a spare connection dataset, we consider that the vertices which can be reached within a short walk steps are all the neighborhood of the starting vertex v, denoted as $Neighbor(v)$. This can help capture the idea that similar vertices usually share common neighbor vertices.

The task of an embedding model is to learn the mapping function Φ: $V \rightarrow \mathbb{R}^d$, where d represents the dimensions and $d \ll |V|$ which is low-dimensional. In the proposed field-aware network embedding, we model the representation from the two perspectives:

1. Φ^1 for modeling the first-order relations, which means the vertices which are connected to each other shall be similar to each other

2. Φ^2 for modeling the second-order relations, which means the vertices which share the common neighbor vertices shall be similar to each other.

The concept of the first-order and second-order relations are the same in [20]. It defines that each vertex plays two roles: the vertex "itself" and a specific "context" of other ver-

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tices. In this work, Φ^1 is for the representation treated as vertex itself, while Φ^2 is the representation treated as a specific context.

Note that the direct learning of the second-order relations may suffer from the relation imbalance issue [5, 6]. To tackle with both the interaction types and relation imbalance issues, we further model Φ^2 with distinct mapping functions when the vertex interacts with different fields. That is, a vertex v_i is mapped by $\Phi^2_{f_{v_j}}(v_i)$ when it interacts with a vertex v_j with field f_{v_j}.

3.2 Field-aware embedding structure

Figure 3.1 (left) is an example of input network with 5 vertices. The user symbols belong to the user type, the others belong to the track type. The proposed field-aware embedding framework can be represented by a single-layer neural network, where the input and output are a vector representation, as the shown in Figure 3.1 (right). In this section, we first discuss why the solution of [12] is not applicable to the existing network embedding models, and then to present our proposed solution.

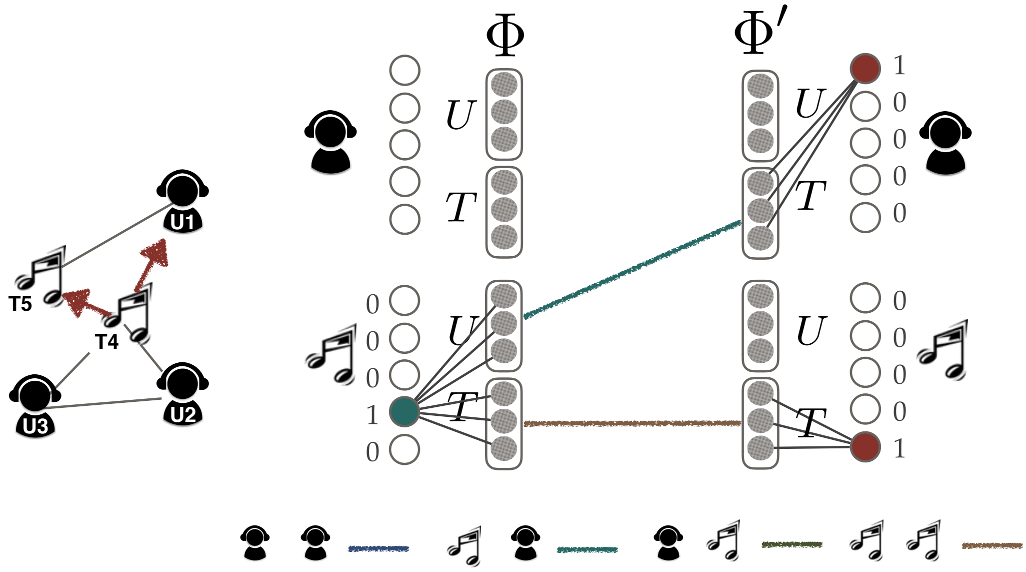

Figure 3.1: The diagram of Multi-Representation Multi-Context

Left: Example network. Right: The model input and context output for pairs in (T_4, U_1) and (T_4, T_5)

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To directly use the solution of [12], it is an idea to modify the modeling structure to be a "Multi-Representation Multi-Context" form like the Figure 3.1 (right). By applying this to the second-order relation embedding, each vertex learns the latent effect from one of other features for both the vertex input and the context output. For instance, for the pairs in (T_4, U_1) and (T_4, T_5) in the example network, we estimate the conditional probability $p(U_1|T_4)$ and $p(T_5|T_4)$ respectively. Consequently, we can observe that there are a total of 4 relationships: user(U)-user(U), user(T)-track(U), track(U)-user(T) and track(T)-track(T). The user compresses the information of user(U) and track(U), and the track compresses the user(T) and track(T), so they are not comparable to each other. In summary, since they compress the information from different latent spaces, the structure of multi-representation multi-context is fail to tackle the incomparable problem.

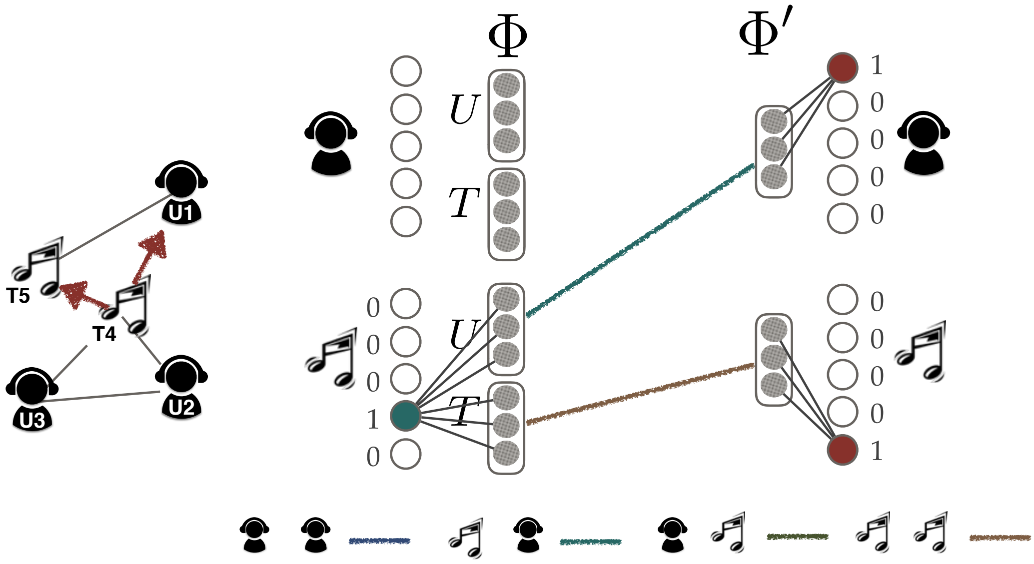

Figure 3.2: The diagram of Multi-Representation Single-Context

Left: Example network. Right: The model input and context output for pairs in (T_4, U_1) and (T_4, T_5)

To avoid learning the information from wrong space, we propose another proper modeling structure: "Multi-Representation Single-Context". Figure 3.2 demonstrates the model of multi-representation single-context. We map the context output with only one output vector. Consequently, we can observe that the 4 relationships become: user(U)-user,

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user(T)-track, track(U)-user and track(T)-track. Therefore, the user compresses the information of user and track, and the track compresses the user and track as well, so they are comparable to each other. Moreover, the information of the interaction types are separately stored in distinct representations (i.e. user/item(U) and user/item(T)).

3.3 Model Description

The embedding model is an attempt to capture the relations among the vertices in a network. Following the embedding learning criteria that the vertices which share common neighbor vertices are supposed to have similar representations, we define the demand similarity probability of an observed pair (v_i, v_j) by follows:

$$p(v_j|v_i) = \begin{cases} 1 & \text{if } v_j \in Neighbors(v_i) \\ 0 & \text{otherwise} \end{cases}. \tag{3.1}$$

To obtain the proper vertex representations in the proposed field-aware embedding model, the first-order relations are modeled the same as the previous work [20] by:

$$\hat{p}(v_j|v_i) = \sigma(\Phi^1(v_i) \cdot \Phi^1(v_j)), \tag{3.2}$$

where σ is the sigmoid function that re-scales the measured distance from 0 to 1. The directly connected are mapped with similar representations.

As to the second-order relations, we map each vertex by the mapping functions Φ^2 for the vertex mapping and $\Phi^{2'}$ for the neighbor mapping. The preceding defined relations can be modeled by measuring the representations distance:

$$\hat{p}(v_j|v_i) = \sigma(\Phi^2(v_i) \cdot \Phi^{2'}(v_j)). \tag{3.3}$$

Consequently, the vertices which share common neighbor vertices will receive closed rep-

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resentations which fit the requirements.

To integrate the filed-aware concept with second-order relations learning, we propose to map a vertex with multiple representations based on the interaction type, called multi-representations single context. The interaction type is depended on the interaction vertex. For a pair (v_i, v_j), the vertex v_i is mapped according the type of the neighbor vertex v_j:

$$\hat{p}(v_j|v_i) = \sigma(\Phi^2_{f_{v_j}}(v_i) \cdot \Phi^{2'}(v_j)). \tag{3.4}$$

To fit the defined requirements in Equation 3.2 and 3.4, the task becomes to minimize the gap between the ground truth $p(v_j|v_i)$ and the estimation function $\hat{p}(v_j|v_i)$. The final objective function is equivalent to minimize following distance function:

$$O = \sum_{(v_i,v_j)\in S} \hat{d}(p(v_j|v_i), \hat{p}(v_j|v_i)), \tag{3.5}$$

where S is the set of sampling pair.

3.4 Model Optimization

We use the KL-divergence to minimize the distance of the ground truth and the estimation function. By replacing $\hat{d}(\cdot,\cdot)$ with KL-divergence and omitting some constants, we have:

$$\begin{aligned} O &= \sum_{(v_i,v_j)\in S} \hat{d}_{KL}(p(v_j|v_i), \hat{p}(v_j|v_i)) \\ &\approx \sum_{(v_i,v_j)\in S^{pos}} - \log \hat{p}(v_j|v_i) + \sum_{(v_i,v_j)\in S^{neg}} \log \hat{p}(v_j|v_i). \end{aligned} \tag{3.6}$$

There are two cases in the derivative objective function. The former one is for modeling positive pairs in S^{pos} and the latter one is for modeling negative pairs in S^{neg}. We adopt the stochastic gradient algorithm (SGD) method to optimize the objective function. In details, it calculates the partial derivative of $\frac{\partial O}{\partial \vec{v}}$ when updates the representation of v in

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a sampling pair. The derivation of v_i in the positive case is:

$$\frac{\partial - \log \hat{p}(v_j|v_i)}{\partial \vec{v_i}} = -(1 - \sigma(\vec{v_i} \cdot \vec{v_j})) \cdot v_j \tag{3.7}$$

The derivation of v_i in the negative case is:

$$\frac{\partial \log \hat{p}(v_j|v_i)}{\partial \vec{v_i}} = \sigma(\vec{v_i} \cdot \vec{v_j}) \cdot v_j \tag{3.8}$$

Note that v_j is updated in a similar way. By iteratively updating the representations according to the sampling pairs in S^{pos} and S^{neg}. The final obtained representations are approximated towards the demand ground truth. Algorithm 1 shows the whole learning procedure. In the following experiments, we update each Φ by the batch SGD.

Algorithm 1: Field-Aware Network Embedding (FNE)

Input: Network Graph: $G(V, E)$ with the Field Set F, Learning Rate: α,
Sampling Times: t

for $v \in V$ **do**
    Initialize the representations: $\Phi^1(v)$, $\Phi^{2'}(v)$
    for $f \in F$ **do**
        Initialize the representations: $\Phi^2_f(v)$

for $counter \in \{1, ..., t\}$ **do**
    for $(v_i, v_j) \in S^{pos}$ **do**
        $\Phi = \Phi - \alpha \times (-(1 - \sigma(\vec{v_i} \cdot \vec{v_j})) \cdot v_j)$
    for $(v_i, v_j) \in S^{neg}$ **do**
        $\Phi = \Phi - \alpha \times \sigma(\vec{v_i} \cdot \vec{v_j}) \cdot v_j$

Output: Vertex representations Φ^1 and Φ^2_f for every f

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Chapter 4

Experiments

We conduct the experiments on three public real-world datasets with three variant machine learning applications, including network reconstruction, multi-label classification and item recommendations.

4.1 Dataset

The conducted experiments include two kinds of network datasets: (1) Network datasets including movielens [10] and last.fm datasets. The statistics is shown in Table 4.1. (2) Language network datasets including 20 newsgroup and DBLP [22]. The summary of datasets in shown in Table 4.2.

- **Movielens**[1]: We use two movielens datasets 1m and 10m. Movielens datasets contain basic user information, such as user age, gender. There are 18 movie genres as movie information, for each movie, it belongs to at least one genre. The rating score of a user given a movie is range from 1 to 5. We only use the rating higher than 3 stars as the positive relations for the following experiment settings. Based on the rating scores, we construct a bipartite network containing the user-movie relation.

[1] https://grouplens.org/datasets/movielens/

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- **Last.fm**[2]: Last.fm is a social music website[3]. The website provides a function that users are able to tag the tags to the artists. In this paper, we use the last.fm dataset provided by hetrec2011. There are three fields in this network, the user, the artist and the tag. In this dataset, there are 1,892 users, 17,632 artists and 11,946 tags. The total edges in this network is 31,470. Based on user-artist and user social datasets, we construct a network contains user-artist relation and user-user relation.

- **20 Newsgroups**[4]: The 20 Newsgroups data set is a collection of approximately 20,000 newsgroup documents, partitioned (nearly) evenly across 20 different newsgroups.

- **DBLP**[5]: Dblp, which contains titles of papers from the computer science bibliography. Follow the same setting in [19], we choose six diverse research fields for classification including “database”, “artificial intelligence”, “hardware”, “system”, “programming languages”, and “theory”. For each field, we select representative conferences and collect the papers published in the selected conferences as the labeled documents.

We build the user-item network based the user preference, and it is a heterogeneous network with two vertex types.

Table 4.1: Statistics of the real-world network datasets.

Name	Field	#Nodes	#Edges	
Movielens 1m	Users	6040	U-M:	1,000,209
	Movies	3900		
Movielens 10m	Users	71567	U-M:	10,000,054
	Movies	10681		
Last.fm (hetrec2011)	Users	1892	U-U:	12,717
	Artists	17632	U-A:	92,834
	Tags	11946	U-A-T:	186,479

[2]https://grouplens.org/datasets/hetrec-2011/
[3]https://www.last.fm/
[4]http://qwone.com/ jason/20Newsgroups/
[5]http://arnetminer.org/billboard/citation

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Table 4.2: Statistics of the language networks.

Name	Size	# words	Doc. length	#Class
20 newsgroup	18846	89039	305.77	20
DBLP	81479	22270	9.51	6

4.2 Compared Algorithms

We use FNE as the abbreviation of the proposed filed-aware network embedding model, and compares the FNE model with several existing graph embedding methods:

- **DeepWalk** [15] is a method that learns the representation of social networks using a sequence of truncated random walks. The truncated random walks, random path, contain high-order information, then using skip-gram to optimize the problem.
- **LINE** [20] learns vertex representations with two defined the skip-gram objective functions to capture the both local and global information. The defined loss functions can preserve the first-order or second-order proximity separately.
- **GraRep** [4] captures successive k-step information through random walk, then factorizing the transition matrix with SVD.
- **PTE** [19] proposed a framework which divide a text heterogeneous network into small networks, learns one relation at a time.

4.3 Evaluation Metrics

In this paper, we conduct 3 machine learning problem to evaluate model performance. We use following metric to evaluate different applications.

- **Recall** (also known as sensitivity) is the fraction of relevant instances that have been retrieved over total relevant instances, which is computed as follow:

$$recall = \frac{\text{\#retrieved relevant documents}}{\text{\#relevant documents}} \tag{4.1}$$

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- **MAP** (mean averaged precision) for a set of queries is the mean of the average precision scores for each query. The formula is showed as follow:

$$MAP = \frac{\sum_{q=1}^{Q} \text{Avg Precision(q)}}{\#Q} \tag{4.2}$$

- **Macro-F1** is a metric which gives equal weight to each class. It is defined as follows:

$$Macro - F1 = \frac{\sum_{A \in C} F1(A)}{|C|}, \tag{4.3}$$

where $F1(A)$ is the F1-measure for the label A and C is the overall label set.

- **Micro-F1** is a metric which gives equal weight to each instance. It is defined as follows:

$$Precision = \frac{\sum_{A \in C} TP(A)}{\sum_{A \in C} TP(A) + FP(A)}, Recall = \frac{\sum_{A \in C} TP(A)}{\sum_{A \in C} TP(A) + FN(A)} \tag{4.4}$$

$$Micro - F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4.5}$$

4.4 Parameter Settings

Our experiments were conducted based on the same criteria. For both movielens rating networks and lastfm tagging network, the dimension is set as 200 by default. In LINE model, 100 dimensions for first-order proximity and second-order proximity. In FNE, we use same ratio for first-order and fields-aware multi-representations for each fields, that is, we set dimensions as 66 for each. Other default settings include: the number of window size win = 5, walk length t = 64, walks per vertex = 28 for DeepWalk; the number of negative samples K = 5, total number of samples T = 10 billion for LINE. Same settings in FNE: the number of negative samples K = 5 and total number of samples T = 10 billions.

As to language networks, we set minimum count as 0, window size as 5 for PTE to construct a word-word network. Then combines the word-word network, word-document

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network and word-label network to compose a text heterogeneous network. As to learning feature representations, we use the same settings for both FNE and PTE: number of samples(T) = 10 billion, negative samples K = 5 and vertex representation D = 200.

4.5 Experiment Results

4.5.1 Network Reconstruction

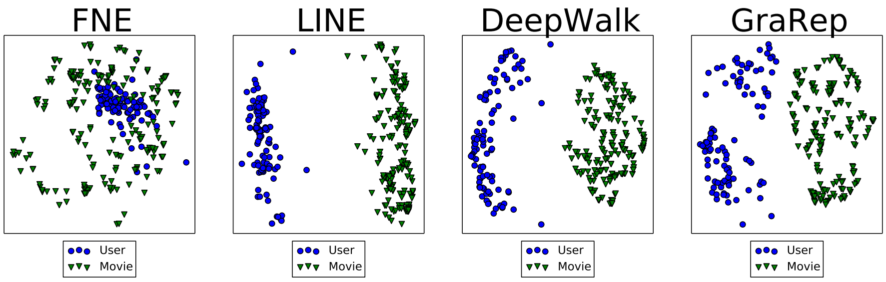

Figure 4.1: The 2-dimensional representations obtained from each baseline model on Movielens-1m.

Network reconstruction is a task to test whether the learned representations are able to reflect the connected relations of the original network. Figure 4.1 is the visualization of the movie rating network (movielens 1m). Both users and movies are mapped to the 2-D space using the t-SNE[6] package with learned embeddings as input. From the visualization results, the vertices in FNE is keeps together, however the others are mapped into the separated areas, because that the vertex representations from other models is learned from different latent spaces. Although bringing the information from high-order might ease up the problem, the learned representations are still affected by the imbalanced ratio of vertex types. This indicates that the existing network embedding models cannot perform well in network reconstruction for certain heterogeneous networks such as the examined user-item network.

In addition to the visualization result, we evaluate the performance of the network reconstruction task by following procedures: (1) Use 80% data as training data, 20% as

[6]http://scikit-learn.org/stable/modules/generated/sklearn.manifold.TSNE.html

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Table 4.3: The network reconstruction results in Movielens datasets (1m & 10m)

Dataset	Movielens-1M				Movielens-10M			
Model	FNE	LINE	GraRep	DeepWalk	FNE	LINE	GraRep	DeepWalk
TopN	N = 10							
Recall@10	**0.2099**	0.0007	0.0167	0.0068	**0.1251**	0.0217	-	0.0192
MAP@10	**0.1081**	0.0001	0.0058	0.0019	**0.0674**	0.0076	-	0.0066
TopN	N = 20							
Recall@20	**0.2192**	0.0008	0.017742	0.0094	**0.1134**	0.0216	-	0.0185
MAP@20	**0.0894**	0.0001	0.0043	0.0017	**0.0483**	0.0052	-	0.0044
TopN	N=30							
Recall@30	**0.2407**	0.0011	0.0186	0.0129	**0.1116**	0.0221	-	0.0186
MAP@30	**0.0852**	0.0001	0.0037	0.0017	**0.0413**	0.0042	-	0.0035

Table 4.4: The network reconstruction results in Last.fm

Model	FNE	LINE	GraRep	DeepWalk
TopN	N = 10			
Recall@10	0.0354	**0.0357**	0.0141	0.0355
MAP@10	0.0178	**0.0191**	0.0084	0.0176
TopN	N = 20			
Recall@20	**0.0413**	0.0397	0.0151	0.0410
MAP@20	0.0151	**0.0162**	0.0076	0.0153
TopN	N=30			
Recall@30	**0.0521**	0.0476	0.0169	0.0506
MAP@30	0.0159	**0.0168**	0.0077	0.0161

testing data. (2) Construct a network from training data and learned vertex representations. (3) Evaluate performance by given one vertex, evaluate the recall@N and MAP@N of retrieved connected edges. We repeat the procedure 5 times and report the average result. The performance is showed as table 4.3 and table 4.4. In movielens networks, our model outperforms all compared methods. However in lastfm network, our model obtains similar performance of LINE and DeepWalk because the dataset provides user-user connections, which alleviates the connection imbalance problem. Please note that the GraRep model is unable to run on Movielens-10M graph with limited memory, so we do not report the result.

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Table 4.5: The multi-label classification results in Movielens datasets (1m & 10m).

Dataset	Movielens-1M				Movielens-10M			
Model	FNE	LINE	GraRep	DeepWalk	FNE	LINE	GraRep	DeepWalk
Train Ratio	10%							
Micro-F1	**0.7513**	0.7001	0.6817	0.7183	**0.6661**	0.6179	-	0.5578
Macro-F1	**0.6589**	0.5544	0.4237	0.6123	**0.5435**	0.4917	-	0.4277
Train Ratio	30%							
Micro-F1	**0.8087**	0.7728	0.7363	0.7568	**0.6934**	0.6581	-	0.6334
Macro-F1	**0.7722**	0.6956	0.5639	0.7008	**0.6934**	0.6581	-	0.6334
Train Ratio	50%							
Micro-F1	**0.8268**	0.7984	0.7543	0.7763	**0.6934**	0.6581	-	0.6334
Macro-F1	**0.8126**	0.7439	0.6161	0.7338	**0.6934**	0.6581	-	0.6334

Table 4.6: The multi-label classification results in Last.fm.

Model	FNE	LINE	GraRep	DeepWalk
Train Ratio	10%			
Micro-F1	0.3992	**0.3996**	0.3164	0.3662
Macro-F1	**0.3642**	0.3542	0.2508	0.3362
Train Ratio	30%			
Micro-F1	**0.4894**	0.4768	0.4431	0.3986
Macro-F1	**0.4511**	0.4409	0.3749	0.3637
Train Ratio	50%			
Micro-F1	**0.5224**	0.5095	0.4732	0.4453
Macro-F1	**0.4876**	0.4805	0.4077	0.4106

4.5.2 Multi-label Classification

This task is to classify the items attributes based on the learned representations. For movielens dataset, we use movie genre as the labels; for last.fm dataset, we use the top 20 artist tags as the labels. Similar to [20, 19], for each class, we train a one-vs-rest logistic regression classifier using the LibLinear package [7]. We use Macro-F1 and Micro-F1 as evaluation metrics. The results are averaged over 5 different runs by sampling different training data. The performance is shown in Table 4.5 and Table 4.6. Again, the GraRep model is unable to run on Movielens-10M graph with limited memory, so we do not report the result. As the table shows, the FNE model outperforms the other models on movielens network. As to lastfm dataset, our model is slightly to lose LINE in train ratio at 10%. However, as the train ratio increase, our model get better results.

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Table 4.7: The item recommendation results in Movielens datasets (1m & 10m).

Dataset	Movielens-1M				Movielens-10M			
Model	FNE	LINE	GraRep	DeepWalk	FNE	LINE	GraRep	DeepWalk
TopN	N = 10							
Recall@10	**0.2099**	0.0007	0.0167	0.0068	**0.1809**	0.0042	-	0.0036
MAP@10	**0.1081**	0.0001	0.0058	0.0019	**0.0954**	0.0014	-	0.0011
TopN	N = 20							
Recall@20	**0.2192**	0.0008	0.0177	0.0094	**0.2199**	0.0047	-	0.0040
MAP@20	**0.0894**	0.0001	0.0043	0.0017	**0.0938**	0.0010	-	0.0008
TopN	N=30							
Recall@30	**0.2407**	0.0011	0.0186	0.0129	**0.2549**	0.0054	-	0.0045
MAP@30	**0.0852**	0.0001	0.0037	0.0017	**0.0966**	0.0008	-	0.0007

Table 4.8: The item recommendation results in Last.fm.

Model	FNE	LINE	GraRep	DeepWalk
TopN	N = 10			
Recall@10	**0.1152**	0.0398	0.0037	0.0702
MAP@10	**0.0563**	0.0186	0.0014	0.0373
TopN	N = 20			
Recall@20	**0.1437**	0.0448	0.0050	0.0758
MAP@20	**0.0522**	0.0157	0.0012	0.0314
TopN	N=30			
Recall@30	**0.1799**	0.0573	0.0064	0.0928
MAP@30	**0.0565**	0.0167	0.0012	0.0330

4.5.3 Link Prediction / Item Recommendations

Link prediction is also called item recommendations in these kind of bipartite networks. Follow the similar procedure in networks reconstruction, (1) we randomly hide a portion of the existing links and train on the remain network. (2) For each user-vertex, we use the learned representation to predict the unobserved links. From the retrieved items, we evaluate the performance by recall@N and MAP@N. Table 4.7 and Table 4.8 lists the scores of the MAP and recall. The results are consistent with the network reconstruction task that the existing network embedding models cannot perform well in neighborhood predictions, while FNE solves the problem.

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Table 4.9: The documents classification results on 20 newsgroup and DBLP datasets.

Dataset	20 newsgroup		DBLP	
Metric	Macro-F1	Micro-F1	Macro-F1	Micro-F1
FNE	**0.4888**	**0.6435**	**0.6849**	**0.7570**
PTE	0.4518	0.6147	0.6760	0.7433

4.5.4 Documents Classification

The document classification task is conducted on text heterogeneous networks, which contains documents, label of documents, and words in documents. This is a special case of heterogeneous networks due to the edges between vertexs is link by people heuristic. Follow the settings in [19], we construct a heterogeneous networks contains three fields, such as words, documents, labels. The evaluate procedure is as follows: (1) Obtain word embeddings from construct language network. (2) Take the average of the word vector representations in that document as document representations. (3) Train a one-vs-rest logistic regression classifier using package (LibLinear [7]). Table 4.9 reports the performance of document classification. From the table, FNE outperforms PTE on both datasets. The result proves that our model can learns better word embeddings without preprocessing the network form.

4.5.5 Experiment Results Summary

Our model focuses on dealing with the incomparable problem in heterogeneous network embedding by modeling different interaction separately. The above experiment results prove the effectiveness of proposed method. Moreover, our model much improves the performance on cross-field problems, such as item recommendation, network reconstruction on bipartite network. The reason is that different type of node representations can be comparable. As to machine learning applications such as classification which only focusing on one type representations, our model can obtain the same or better results than other baseline methods.

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Chapter 5

Discussion

In this chapter, we construct several experiment to examine different factor affected the model, such as model parameters and the dimension of fields.

5.1 Parameter Sensitive

In this section, we analyze the model performance respect with parameter sensitivity.

5.1.1 Performance w.r.t. #Samples

The time complexity of our model is $O(tsd)$, where t is the number of iteration, s is the number of negative samples and d is the dimension of representations. The number of s and d are usually smaller than t, therefore, the converging performance of model is mainly affect by iterations. Figure 5.1 shows the results of two machine learning applications w.r.t. #samples on Movielens-1m datasets. We can know that our model is converge at early stages.

5.1.2 Performance w.r.t. Dimension

The field-aware network embedding algorithm provides multi-representations for each fields. As a result, the dimension can be divide into several parts, vector for first-order

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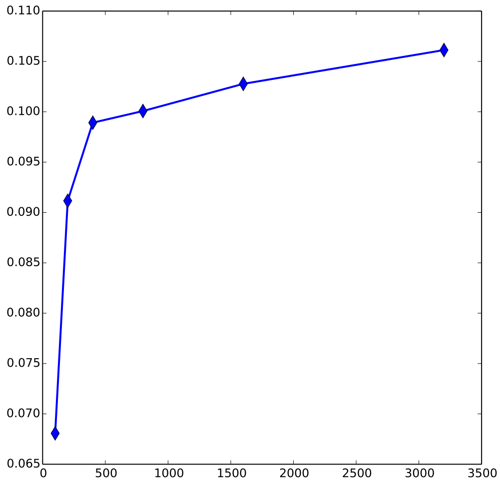
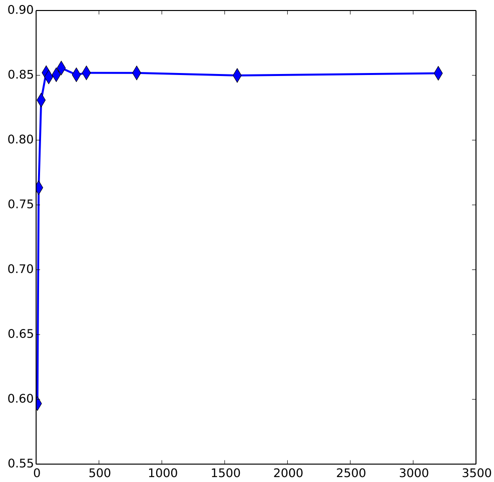


(a) The link prediction result w.r.t. #samples.



(b) The multi-label classification result w.r.t. #samples.

Figure 5.1: The performance of two machine learning applications w.r.t. #samples on Movielens-1m datasets.

used to capture direct relations in network; vector for $field_1$ used to capture the latent from $field_1$; $field_2$ used to capture the latent from $field_2$, ..., etc. As the number of field increase, the vertex representations would be divide into many small segments. If the dimension is too small, the representations is unable to represents the vertex well. Figure 5.2 shows the performance of multi-label classification respect with the number of dimension. Although when the dimension is small, our model is fail to surpass other models, as we gradually increase the dimension of representations, our model begins to outperform other methods.

5.1.3 Performance w.r.t. Network Sparsity

We investigate how the sparsity of the networks affects the models. Figure 5.3 shows the results w.r.t. the degrees of the vertices on movielens 1m and 10m datasets. We categorize the vertices into different groups according to their degrees including $(0, 1]$, $[2, 4]$, $[5, 8]$, $[9, 16]$, $[17, 32]$, $[33, \infty)$ and then evaluate the performance of vertices in different groups. Overall, the performance of different models increases when the degrees of the

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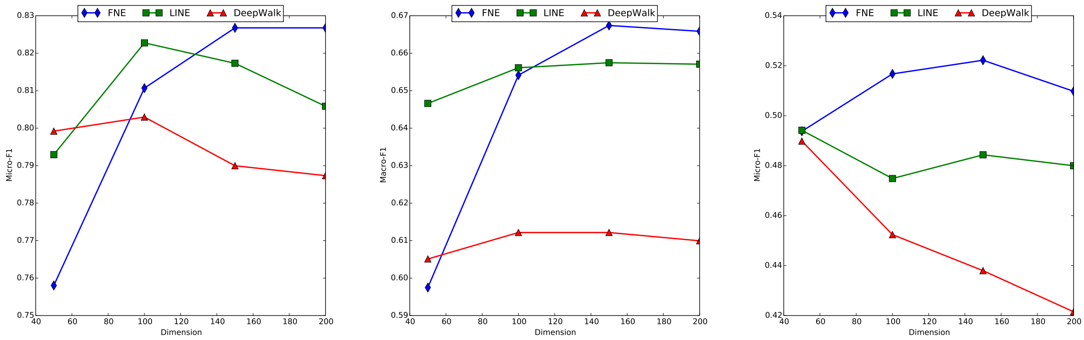
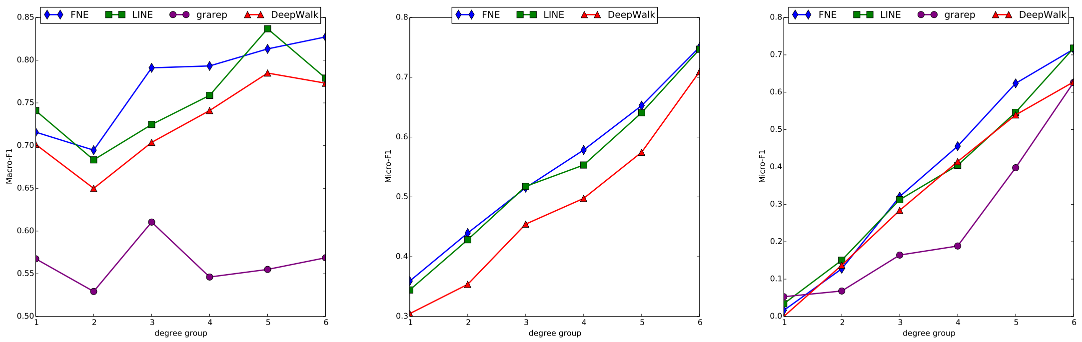


(a) ML-1m (b) ML-10m (c) Last.fm

Figure 5.2: The multi-label classification result w.r.t. Dimension on three datasets.



(a) ML-1m (b) ML-10m (c) Lastfm

Figure 5.3: The multi-label classification result w.r.t. Degree of vertices on three datasets.

vertices increase. The LINE outperforms FNE in the first group because that that LINE optimizes only the directly connected vertices and does not add the information from high-order. The performance in ML-10m is more stable than ML-1m, because the amount of data records. Our model obtains the same or better results than LINE in ML-10m. We can also see that our model outperforms DeepWalk and GraRep in all the groups.

5.2 Dimension of Fields

In this section, we investigate how the dimension of different fields affect the performance. We set user dimension range from 0 to 100, item dimension range from 0 to 100, then conduct two machine applications (multi-label classification and link prediction) to evaluate the performance. Figure 5.4 shows the performance of two machine applications

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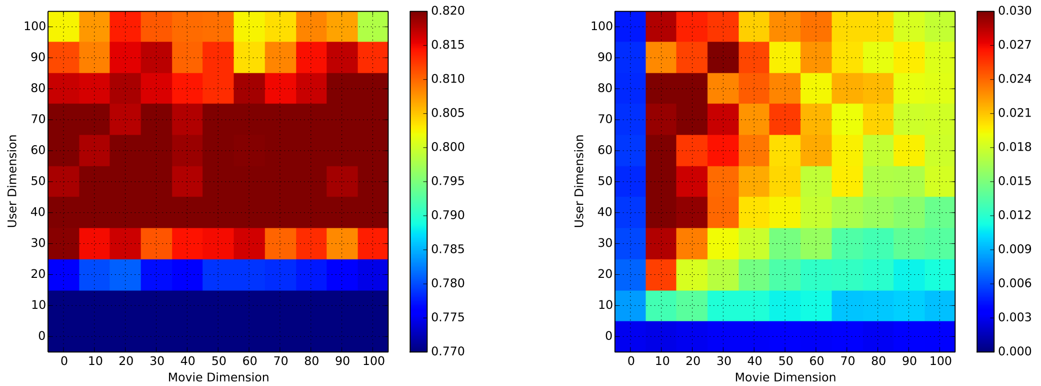

(a) Multi-label Classification (Micro-F1) (b) Link Prediction (MAP)

Figure 5.4: The performance w.r.t User-Movie dimensions on ML-1m.

w.r.t different User-Movie dimension pair on Movielens 1m dataset. From two figures, we find that the dimension of movies as $20 \sim 30$ can obtain the best result, the dimension higher than this range might overfit the training data. On the other hand, the dimension need of user is range $40 \sim 70$ in multi-label classification task and $35 \sim 80$ in link prediction task. The most interesting is that we only use the learned movie representations to train a classifier in multi-label classification task, the model without user information get the worst performance. In link prediction task which needs both user-representations and movie-representations, the model without any information get the worst performance.

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Chapter 6

Conclusion

In this paper, we propose a field-aware network embedding that models the rich iteration information from heterogeneous network. The proposed model use the "Multi-Representation Single Context" structure which models the different types of interactions separately and generates low dimension vertices representations for each field. Our model not only can learns iteration from different type without pre-process network but also dealing with the incomparable problem of different type of nodes. Also, the structure of our model makes us able to set different field dimension which provides more flexibility and explanation of data.

The experimental results on various networks show that it is able to improve the representation capability of machine learning applications such as network reconstruction, multi-label classification and link prediction. Moreover, our model have much improve the performance of cross-field problem such as recommendation than other network embedding methods.

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