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E-mail: jzus@zju.edu.cn

Supplementary materials for

Qianqiao LIANG, Hua WEI, Yaxi WU, Feng WEI, Deng ZHAO, Jianshan HE, Xiaolin ZHENG, Guofang MA, Bing HAN, 2023. Exploring financially constrained small- and medium-sized enterprises based on a multi-relation translational graph attention network. *Front Inform Technol Electron Eng*, 24(3):388-402.
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1 Exploratory analyses

In this section, we conduct in-depth exploratory analyses based on an industrial bank dataset collected from MYbank and discover the financing needs transfer patterns in the small- and medium-sized enterprise (SME) graph.

The dataset contains 42.45 million SMEs and 1.26 billion relations among the SMEs. Specifically, we discuss SMEs that bought a loan product as financially constrained SMEs; otherwise, they are financially sufficient. The details of the analyses are elaborated as follows.

1.1 Correlation between SMEs' relations and financing needs

To explore the correlation between SMEs' relations and their financing needs, we conduct two statistical analyses based on six randomly chosen relation types, i.e., affiliated, parent, supplier, stock owner, stock guarantor, and joint owner.

In the first statistical analysis, we first separate the SMEs into a financially constrained group and a financially sufficient group; we then calculate the ratio of the number of SMEs that have previously financially constrained neighbors to the size of each group. The results are shown in Fig. S1. Obviously, under the six types of relations, financially constrained SMEs are more likely to have previously financially constrained neighbors, which indicates the importance of SMEs' relations on their financing needs.

In the second statistical analysis, we investigate the correlation between the financing needs of SMEs and the number of their financially constrained neighbors. Specifically, under each relation, we group SMEs by the number of financially constrained neighbors that they have and report the ratio of financially constrained SMEs in each group. The results are shown in Fig. S2. It is worth noticing that the more financially constrained neighbors an SME has, the more likely it is that the investigated SME is also financially constrained, which indicates that relations among SMEs have a great impact on SMEs' financing needs.

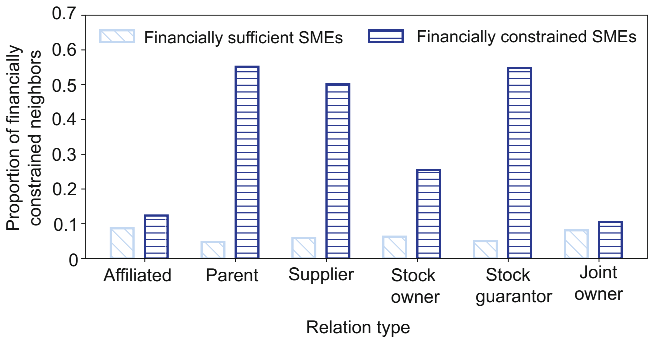

Fig. S1 Comparison of financially constrained neighbors under two different SME groups (SME: small- and medium-sized enterprise)

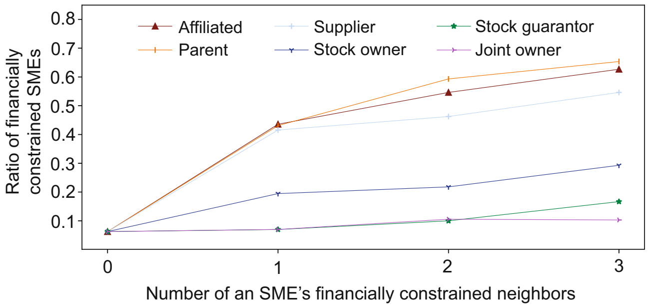

Fig. S2 Comparison of ratios of financially constrained SMEs under different SME groups (SMEs in each group have a specific number of financially constrained neighbors; SME: small- and medium-sized enterprise)

The results of the above statistical analyses demonstrate that connected SMEs tend to have similar financing conditions, which verifies the necessity of modeling SMEs' relations in the financing needs exploration (FNE) task.

1.2 Financing needs transfer under heterogeneous relations

We further investigate the results under different relation types. Interestingly, the proportions in Fig. S1 are different under various relation types. The differences in the results under the six relation types are even more significant in Fig. S2, which demonstrates that the transferred messages are heterogeneous under different types of relations. This observation motivates us to pay attention to transfer heterogeneity when modeling the SME graphs.

In addition, we discover that the relations in the SME graphs have multi-structure properties. For example, the relation types "affiliated," "parent," and "stock guarantor" have a one-to-many mapping structure; the "stock owner" and "supplier" are structured to have many-to-many mapping; whereas the relation type "joint owner" is structured as many-to-one mapping. In addition, each SME has more than two types of relations on average. These observations indicate that each SME may have different roles and behave differently under different relation types. Such behavior heterogeneity is common in a real enterprise social network, which motivates us to allow heterogeneous representations of each SME under different relation types.

2 Notations

We provide the main notations in Table S1.

Table S1 Main notations of our proposed M-RIGHT

Notation	Description
$\boldsymbol{h}_i^l \in \mathbb{R}^{d_l}$	Node i's input feature in the l^{th} layer
$\boldsymbol{r}_i^l \in \mathbb{R}^{d_l}$	Relation i's input feature in the l^{th} layer
L	Total number of layers
K	Total number of attention heads
$\mathcal{N}(h)$	Neighbor set of node h
$\mathcal{T}(i,j)$	Relation type between nodes i and j
$\boldsymbol{W}_{h,k}^l \in \mathbb{R}^{d_l \times \frac{d_{l+1}}{k}}$	Node transformation metric in the k^{th} attention head of the l^{th} layer
$\boldsymbol{W}_r^l \in \mathbb{R}^{d_l \times d_{l+1}}$	Relation transformation metric in the l^{th} layer
$\boldsymbol{W}_w^l \in \mathbb{R}^{d_l \times d_{l+1}}$	Relational hyperplane transformation metric in the l^{th} layer
$\boldsymbol{w}_r^l \in \mathbb{R}^{d_l}$	Hyperplane's projection vector for relation type r in the l^{th} hidden layer

M-RIGHT: Multi-relation tRanslatIonal GrapH aTtention network

3 Analysis of M-RIGHT

Here we give the analysis of our proposed M-RIGHT as follows:

(1) The proposed M-RIGHT is able to effectively address the transfer heterogeneity by calculating the neighbors' attentions and the transferred messages based on our devised entity–relation composition operator, which distinguishes heterogeneously transferred messages from different relation types.

(2) The proposed M-RIGHT is able to address the behavior heterogeneity based on the translation mechanism on relational hyperplanes, which enables each SME to have distinguishable representations under different relation types.

(3) The modeling of SMEs and various relation types is based on shared parameters, which alleviates the inefficient problem of over-parametrization while applying graph convolution networks on relational graphs and allows any available feature as initial representations.

4 More details of experimental settings

4.1 Financing needs exploration (FNE) scenario in MYbank

MYbank is an online financial platform that provides financial loan services to SMEs. Because SMEs' credits have been validated as a separate task, the main focus of the FNE task in MYbank is to target financially constrained SMEs among the credit-validated SMEs. Then, MYbank launches some marketing campaigns on those targeted SMEs, such as presenting a loan product on the owner's homepage of the application program (APP) or sending short messages through short messaging service (SMS) to those SMEs' owners. Then, the feedback of whether the targeted SMEs have bought a loan product afterward is collected as offline datasets, in which the SMEs that bought a loan product are regarded as financially constrained SMEs. In other words, two datasets, i.e., the APP dataset and the SMS dataset, are available to verify the effectiveness of our proposed method. Note that the data used in the experiments are sampled from the server's logs, and we have performed data desensitization to ensure that any private and sensitive SME information cannot be extracted from these data.

In the two datasets, the initial node features are the attributes and historical behaviors of SMEs, whereas the initial relation features are randomly generated, which are used as inputs for the graph representation learning model.

4.2 Evaluation metrics

Classification accuracy (CA) summarizes the performance of a classification model as the number of correct predictions divided by the total number of predictions. The micro-averaged F1 (micro-F1) score is used to assess the quality of our binary classification problems, which measures the F1 score of the aggregated contributions of the two classes. The area under the receiver operating characteristic (ROC) curve (AUC) is equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one. In summary, higher values of the three metrics indicate better performance.

4.3 Implementation details

We implement all graph representation learning methods in TensorFlow with the Adam optimizer (Kingma and Ba, 2015) and set the hyperparameters according to the best results in the validation set. All the graph convolution networks in the comparison models involve two convolution layers, each of which computes 128 features ($d_1 = d_2 = 128$) as the output, followed by an exponential linear unit nonlinearity. For the graph attention network (GAT) and M-RIGHT, the attention head is set to be "2," each of which computes 64 features. All methods are trained on a cluster of 15 dual-central processing unit (CPU) servers with automotive grade Linux (AGL) framework (Zhang et al., 2020). We use early stopping with a patience of 100; i.e., we stop training if the loss does not decrease for 100 consecutive epochs. Results of all experiments are averaged over 10 runs.

5 Case study

To intuitively demonstrate the capabilities of M-RIGHT, we conduct a case study of the results predicted by it on six randomly selected SMEs in the APP dataset.

In Table S2, given a specified pair of a head SME s and a tail SME o, we present the top four relations with M-RIGHT's highest predicted triplet scores $f_r(\boldsymbol{h}_s, \boldsymbol{h}_o)$ and the predicted FNE label of each SME. From Table S2, we can draw two conclusions. First, M-RIGHT is able to assign higher scores to ground-truth triplets and exploit relations between SMEs correctly. Such effectiveness relies highly on M-RIGHT's accuracy in learning not only the heterogeneous relation representations but also SME's heterogeneous representations on different relational hyperplanes. Second, M-RIGHT is accurate in predicting SMEs' financing need labels, which indicates that the learned SMEs' representations can well facilitate the FNE task.

Interestingly, we observe that even though SME 2 is connected with SME 1 and SME 3, the predicted label of SME 2 is the same as that of SME 1, while being different from that of SME 3. By analyzing SME 2's projection representations on the relations "subsidiary" (denoted as r_1), "upstream" (denoted as r_2), and "share holder" (denoted as r_3), we find that $||\boldsymbol{h}_{\mathrm{SME2}\perp r_2}||_2 > ||\boldsymbol{h}_{\mathrm{SME2}\perp r_1}||_2 > ||\boldsymbol{h}_{\mathrm{SME2}\perp r_3}||_2$, which means that SME 2 has larger sub-component on r_2's hyperplane, thereby being more affected by the message from r_2, i.e., the message from SME 1, compared to the effect of messages from SME 3. This may explain why the prediction on SME 2 is the same as that of SME 1. A similar phenomenon can be observed for SMEs 4, 5, and 6, and a similar conclusion can be drawn that SME 5 is more affected by the message from the relation type "subsidiary" than those from "upstream" and "share holder." This interesting observation indicates that each SME may have different "sensibilities" under different relations. Therefore, allowing SME's heterogeneous representations under different relation types can facilitate the effective representation learning of SMEs.

Table S2 Case study of six SMEs from two industries

SME pair	Top four relations	Predicted labels
s: Fabric purchase SME 1 o: Fiber preprocess SME 2	(1) Money transfer (2) **Upstream** (3) Purchase (4) Parent	SME 1: $\boldsymbol{y=1}$ SME 2: $\boldsymbol{y=1}$ SME 3: $\boldsymbol{y=0}$
s: Clothing design SME 3 o: Fiber preprocess SME 2	(1) **Subsidiary** (2) **Share holder** (3) Client (4) Upstream	
s: Technology SME 4 o: Electronics SME 5	(1) **Subsidiary** (2) Invoice (3) **Share holder** (4) Stock guarantor	SME 4: $\boldsymbol{y=1}$ SME 5: $\boldsymbol{y=1}$ SME 6: $\boldsymbol{y=0}$
s: Server manufacturer SME 6 o: Electronics SME 5	(1) Invoice (2) **Upstream** (3) Joint venture (4) Contrast	

The bold results mean that the predicted results hit the ground truths. "o" denotes the tail SME; "s" denotes the head SME. SME: small- and medium-sized enterprise

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