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Exploring financially constrained small- and medium-sized enterprises based on a multi-relation translational graph attention network

Key words: Financing needs exploration; Graph representation learning; Transfer heterogeneity; Behavior heterogeneity

Xiaolin ZHENG
E-mail: xlzheng@zju.edu.cn
ORCID: https://orcid.org/0000-0001-5483-0366

Background: Financing needs exploration (FNE)

- With the outbreak of crises such as COVID-19 pandemic and geopolitical wars, more and more small- and medium-sized enterprises (SMEs) are facing financial stress and are in need of financing.
- Financing needs exploration (FNE): A task that financial institutions exploit those financially constrained SMEs, which is significant for facilitating the development of those struggling SMEs.
- Financing needs will transfer among SMEs within the enterprise social network. Therefore, it is of utmost necessity to formulate FNE as a graph representation learning based classification task, which first learns SME representations in the SME graph and then leverages such representations for classification.

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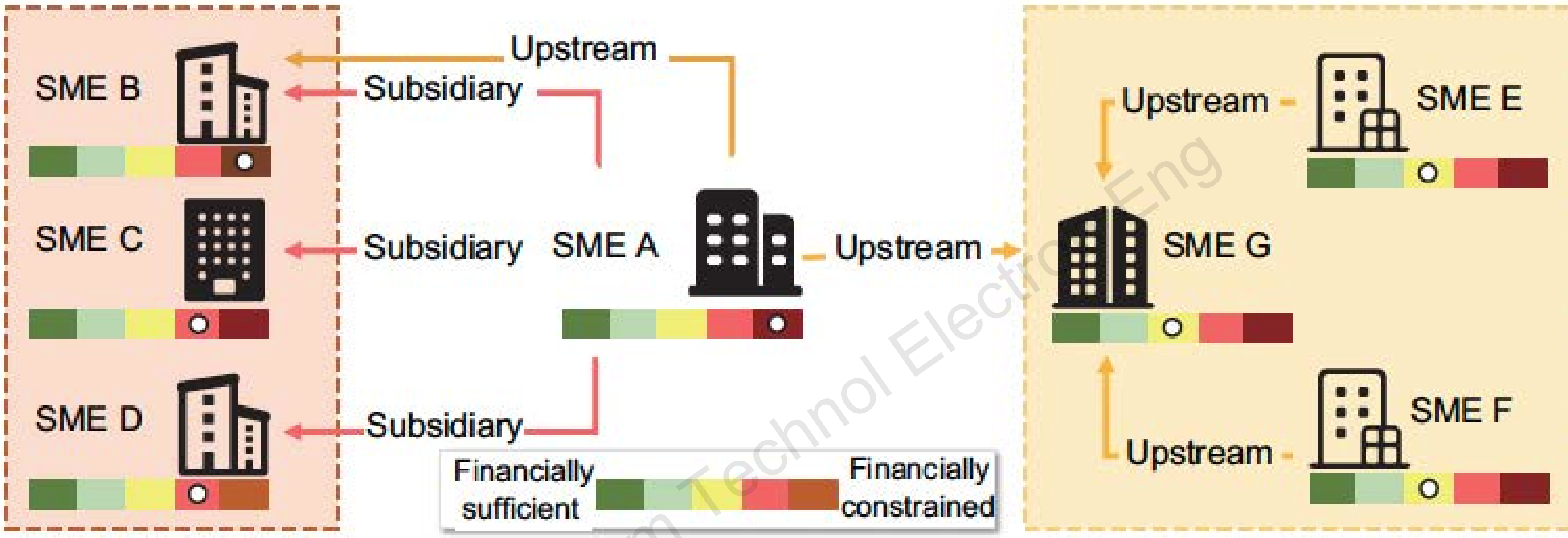
Motivation: Challenges for FNE



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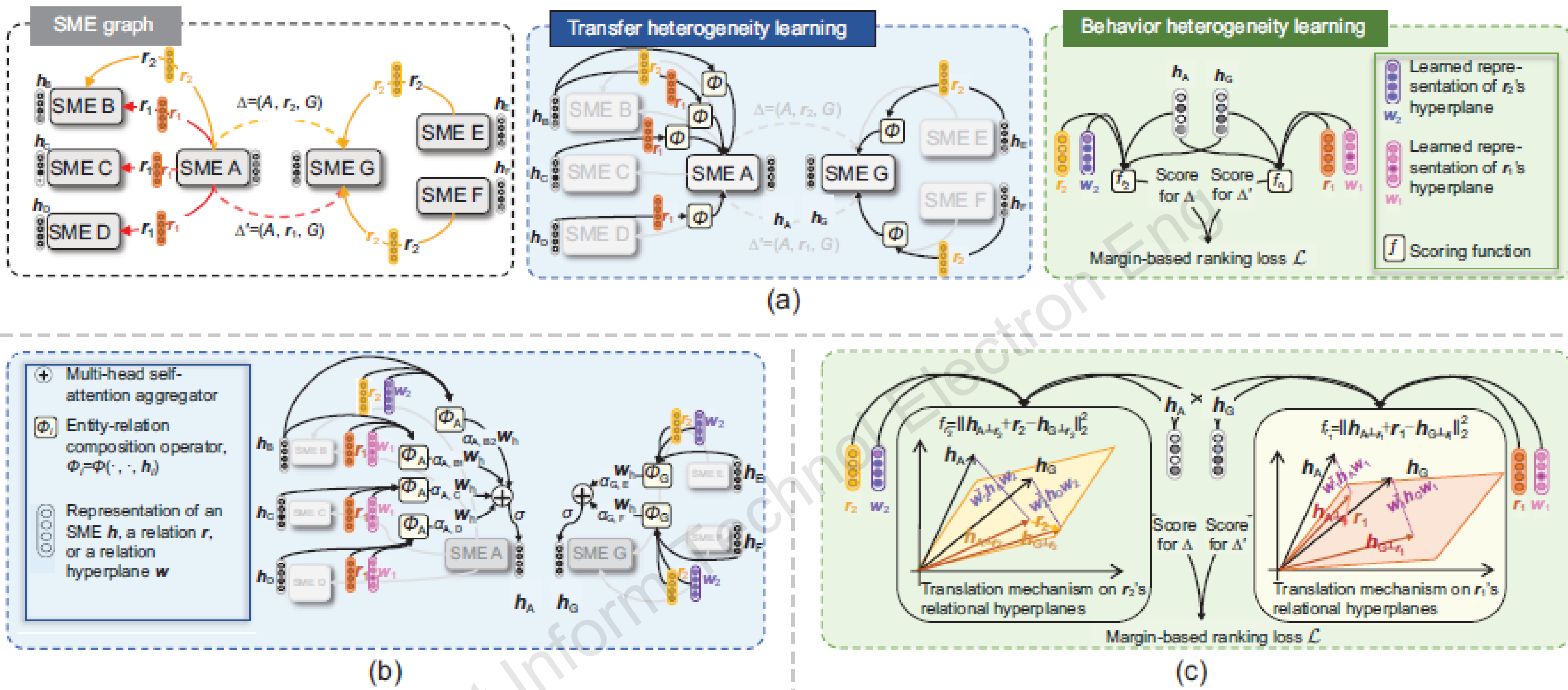
- Transfer heterogeneity: the financing needs transfer differently under different relation types.
- Behavior heterogeneity: each SME behaves differently; i.e., plays different roles, under different relation types.

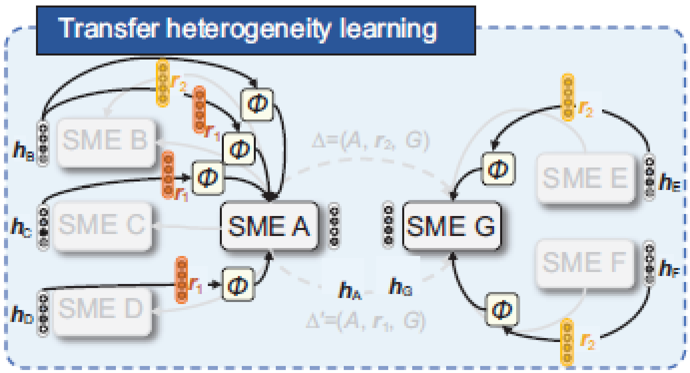
Method: MRIGHT's architecture

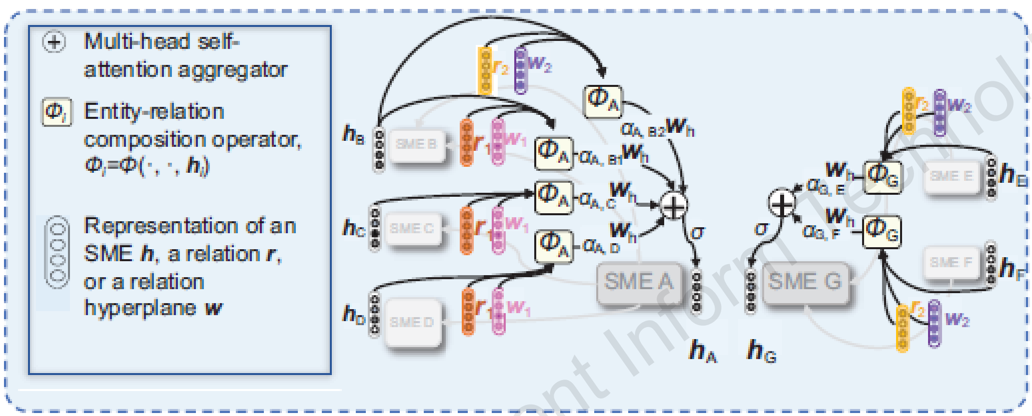


(a)
(b)
(c)

Given an SME graph with initial SME representations $\boldsymbol{h}_*$, relation features $\boldsymbol{r}_*$, a true triplet $\triangle$, and a fake triplet $\triangle'$, M-RIGHT first leverages the transfer heterogeneity learning module to obtain the corresponding SME representations, and then leverages the behavior heterogeneity learning module to obtain the triplets' scores and the corresponding loss for the model's update.

Method: Transfer heterogeneity learning





Obtain representations of SMEs based on the entity–relation composition operator, which distinguishes heterogeneous transferred messages under different relation types.

Algorithm 1 M-RIGHT's representation learning process

Input: SME graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \triangle, \boldsymbol{H}, \boldsymbol{R})$; depth L; number of attention heads K; neighborhood function $\mathcal{N}: h \rightarrow 2^{\mathcal{V}}$

Output: Final representations of SMEs $\{z_i, \forall i \in \mathcal{V}\}$

```
while not converged do
  # Embedding of each layer
  for l = 0, 1, ..., L do
    # Attention under each head
    for k = 1, 2, ..., K do
      # Representation of each SME
      for u ∈ V do
        # Attention of each neighbor
        for v ∈ N(u) do
          e^k_{u,v} = a(W^l_{h,k} h^l_u, W^l_{h,k} Φ(h^l_v, r^l_{T(i,j)}, h^l_u))
          α^k_{u,v} = softmax_v(e^k_{u,v})
        end for
      end for
    end for
    h^{l+1}_u = ||^K_{k=1} f(Σ_{v∈N(u)} α^k_{u,v} W^l_{h,k} ·Φ(h^l_v, r^l_{T(u,v)}, h^l_u))
    ∀i ∈ E, r^{l+1}_i = f(W^l_r r^l_i)
    ∀i ∈ E, w^{l+1}_i = f(W^l_w w^l_i)
  end for
  ∀u ∈ V : z_u = h^{L+1}_u
  # Backpropagation with loss
  L = Σ_{(s,r,o)∈△, (s',r',o')∈△'} [f_r(z_s, z_o) + γ − f_{r'}(z'_s, z'_o)]_+
      + C { Σ_{v∈V} [||z_v||_2^2 − 1]_+ + Σ_{r∈E} [ (w_r^T r_r^{L+1})^2 / ||r_r^{L+1}||_2^2 − ε^2 ]_+ }
end while
```

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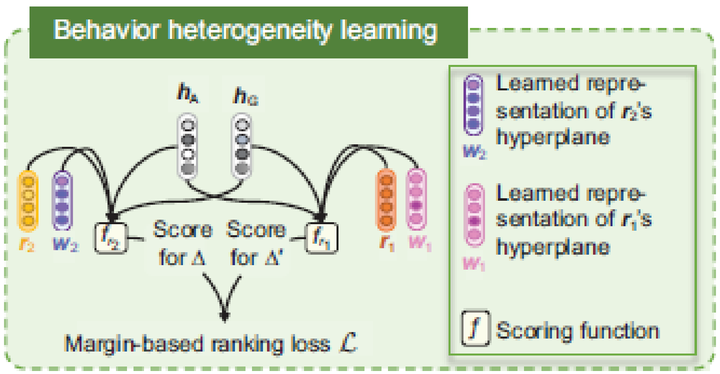
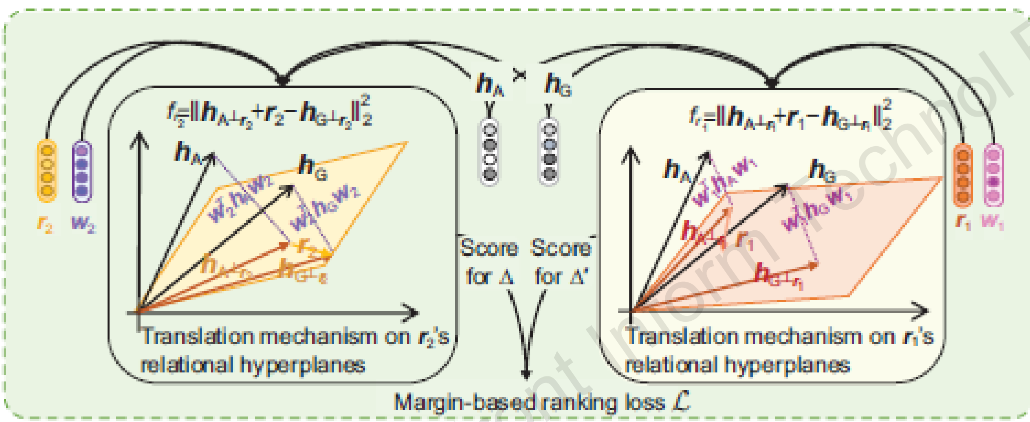
Method: Behavior heterogeneity learning





Scoring function in behavior heterogeneity learning to obtain triplets' scores, which enable heterogeneous representations of SMEs under different relations

Algorithm 1 M-RIGHT's representation learning process

Input: SME graph $\mathcal{G}=(\mathcal{V},\mathcal{E},\triangle,\boldsymbol{H},\boldsymbol{R})$; depth L; number of attention heads K; neighborhood function $\mathcal{N}: h \to 2^{\mathcal{V}}$

Output: Final representations of SMEs $\{z_i, \forall i \in \mathcal{V}\}$

```
while not converged do
  # Embedding of each layer
  for l = 0, 1, ..., L do
    # Attention under each head
    for k = 1, 2, ..., K do
      # Representation of each SME
      for u ∈ V do
        # Attention of each neighbor
        for v ∈ N(u) do
          e^k_{u,v} = a(W^l_{h,k} h^l_u, W^l_{h,k} Φ(h^l_v, r^l_{T(i,j)}, h^l_u))
          α^k_{u,v} = softmax_v(e^k_{u,v})
        end for
      end for
    end for
    h^{l+1}_u = ||^K_{k=1} f(Σ_{v∈N(u)} α^k_{u,v} W^l_{h,k} · Φ(h^l_v, r^l_{T(u,v)}, h^l_u))
    ∀i ∈ E, r^{l+1}_i = f(W^l_r r^l_i)
    ∀i ∈ E, w^{l+1}_i = f(W^l_w w^l_i)
  end for
  ∀u ∈ V : z_u = h^{L+1}_u
  # Backpropagation with loss
  L = Σ_{(s,r,o)∈△, (s',r',o')∈△'} [f_r(z_s, z_o) + γ − f_{r'}(z'_s, z'_o)]_+
      + C { Σ_{v∈V} [||z_v||^2_2 − 1]_+ + Σ_{r∈E} [ (w_r^T r_r^{L+1})^2 / ||r_r^{L+1}||^2_2 − ε^2 ]_+ }
end while
```

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Major results

Table 2 Performance of all methods on CA, micro-F1, and AUC values (mean±range, computed across 10 runs)

Category	Method	APP		
		CA	Micro-F1	AUC
Graph-free methods	ANOVA-XGBoost	0.6688±0.006	0.2303±0.035	0.8585±0.012
	SVM-RE	0.5072±0.005	0.1794±0.026	0.5567±0.022
	DeepFM	0.5821±0.005	0.2041±0.029	0.8344±0.033
Graph-based methods	GIN	0.6708±0.000	0.2344±0.005	0.8550±0.001
	GraphSAGE	0.6645±0.001	0.2302±0.004	0.8601±0.000
	GAT	0.6752±0.000	0.2377±0.005	0.8649±0.000
	RGCN	0.6697±0.001	0.2294±0.005	0.8648±0.001
	CompGCN	0.6695±0.001	0.2295±0.007	0.8660±0.001
	MHGCN	0.6690±0.007	0.2305±0.011	0.8659±0.002
	HRAN	0.6761±0.001*	0.2395±0.006*	0.8664±0.004*
Our proposed methods	M-RIGHT	0.6906±0.001	0.2456±0.007	0.9006±0.001
	M-RIGHT-w/o-rt	0.6760±0.001	0.2382±0.009	0.8788±0.001
	M-RIGHT-w/o-rs	0.6743±0.001	0.2334±0.007	0.8737±0.001
Improvement (%)[1]		2.1447	2.5470	3.9474
p-value[2]		0.000	0.004	0.000

Category	Method	SMS		
		CA	Micro-F1	AUC
Graph-free methods	ANOVA-XGBoost	0.9780±0.002	0.4094±0.003	0.9306±0.000
	SVM-RE	0.9803±0.002	0.1078±0.001	0.7324±0.000
	DeepFM	0.9769±0.002	0.3668±0.002	0.9234±0.001
Graph-based methods	GIN	0.9783±0.001	0.4110±0.001	0.9289±0.000
	GraphSAGE	0.9724±0.001	0.4141±0.002	0.9285±0.001
	GAT	0.9833±0.001	0.4094±0.001	0.9275±0.000
	RGCN	0.9752±0.003	0.4152±0.003*	0.9336±0.001
	CompGCN	0.9828±0.003	0.4120±0.004	0.9298±0.001
	MHGCN	0.9835±0.001*	0.4133±0.001	0.9312±0.000
	HRAN	0.9831±0.004	0.4150±0.007	0.9338±0.001*
Our proposed methods	M-RIGHT	0.9841±0.000	0.4287±0.003	0.9469±0.001
	M-RIGHT-w/o-rt	0.9790±0.002	0.4158±0.003	0.9339±0.000
	M-RIGHT-w/o-rs	0.9830±0.003	0.4181±0.002	0.9368±0.000
Improvement (%)[1]		0.0610	3.2514	1.4029
p-value[2]		0.001	0.000	0.000

APP: application program; SMS: short messaging service; CA: classification accuracy; Micro-F1: micro-averaged F1 score; AUC: area under the receiver operating characteristic (ROC) curve. [1] Improvement of M-RIGHT over the best-performing comparison methods. [2] Statistical improvement over the best-performing comparison methods if p-value<0.05 (p-value with paired t-test). * Results of the best-performing comparison methods

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- M-RIGHT outperforms the state-of-the-art methods in FNE.
- Transfer heterogeneity learning module and behavior heterogeneity learning module contribute to M-RIGHT's performance

Major results (Cont'd)

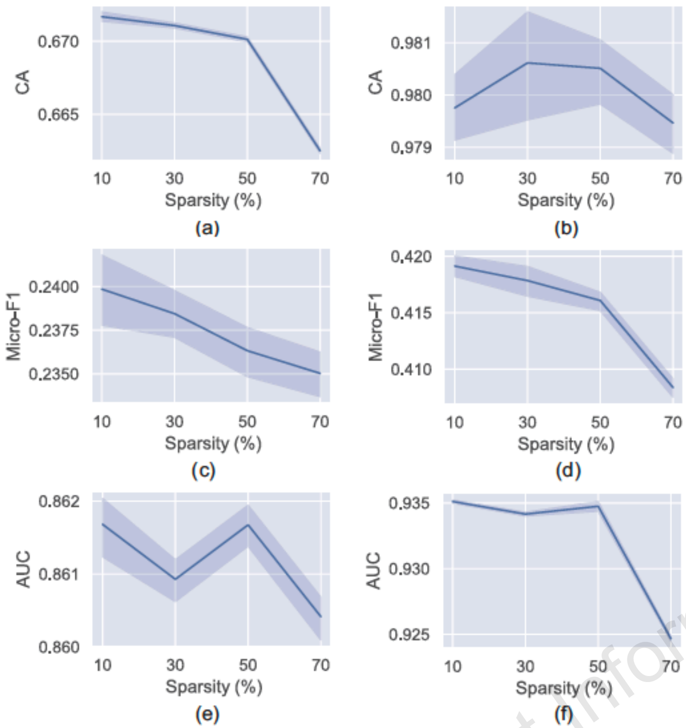

Fig. 3 Performance of M-RIGHT under different dataset sparsities (mean±range, computed across 10 runs): (a) CA on APP; (b) CA on SMS; (c) Micro-F1 on APP; (d) Micro-F1 on SMS; (e) AUC on APP; (f) AUC on SMS (CA: classification accuracy; Micro-F1: micro-averaged F1 score; AUC: area under the receiver operating characteristic (ROC) curve; APP: application program; SMS: short messaging service)

Table 3 Phenomenon with respect to sparisity

Dataset	Relation density	Improvement of modeling relations	Degradation of missing relations
APP	30.07%	15.11%	0.69%
SMS	61.10%	16.37%	1.21%

APP: application program; SMS: short messaging service

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- Performance degradation under more relation-dependent scenarios is more severe.
- M-RIGHT outperforms the graph-free methods even under the sparsest training dataset.

Conclusions

- We have conducted exploratory analysis on the financing needs exploration task, which indicates the importance of modeling SMEs’ relations.
- We have proposed a novel method named M-RIGHT, whose main novelty is that it simultaneously addresses two kinds of challenging heterogeneity, i.e., transfer heterogeneity and behavior heterogeneity, in modeling SME graphs with multiple relations.
- Comprehensive experiments on two real-world datasets have demonstrated the superiority of M-RIGHT to the state-of-the-art methods in exploring financially constrained SMEs.

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Qianqiao LIANG is currently an algorithm engineer at MYbank, Ant Group. Before that, She got her Ph.D. degree in Computer Science and Technology at Zhejiang University in 2023 and got her B.Sc. degree in Software Engineering at Sun Yat-sen University in 2017. Her research interests are in financial intelligence, statistical machine learning, and recommender systems.

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Hua WEI received the Master degree in Computer Science and Technology from Hohai University, China, in 2016. He is currently working as a senior algorithm engineer in MYbank, Ant Group. His research interests are in machine learning, computational advertising, recommendation system, and knowledge graph mining.

Yaxi WU received the Master degree in Control Science and Engineering from Tongji University, China, in 2018. He is currently working as a senior algorithm engineer in MYbank, Ant Group. His research interests are financial knowledge graph and marketing algorithm.

Feng WEI is a staff engineer in MYbank, Ant Group as an NLP team lead. He received the Master degree from Fudan University. His research interests are knowledge graph, dialog system and information extraction and their applications in finance risk control and recommender system.

Deng ZHAO is a staff engineer in Ant Group. He received his B.Sc. degree from Jilin University, and Ph.D. degree from Peking University. His research interests are NLP, knowledge graph and their applications in Internet security, recommender system and Internet finance.

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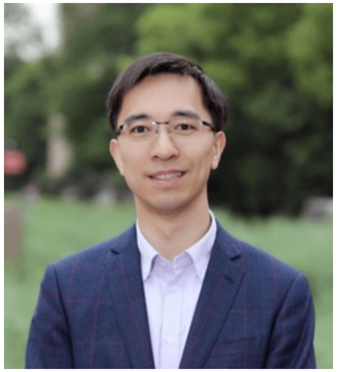
Jianshan HE is a staff engineer in Ant Group, as knowledge graph algo-team lead. He received his B.Sc. degree from South China University of Technology, and the MASc degree from Peking University. His research interests are NLP, knowledge graph, reinforcement learning and their applications in recommender system and Internet finance.



Xiaolin ZHENG is a PhD, Professor, PhD supervisor, and the deputy director of Institute of Artificial Intelligence, Zhejiang University. He is also a senior member of IEEE, and Distinguished Member of China Computer Federation, a Committee Member in Service Computing of China Computer Federation. His main research interests include recommender systems, privacy-preserving computing, and intelligent finance.

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Guofang MA was born in China in 1991. She received Ph.D. degree from Zhejiang University in June 2021. Now she is a lecturer in College of Computer Science and Technology, Zhejiang Gongshang University, China. Her research interest includes social network analysis, transfer learning, deep learning, and cross-domain recommender system.

Bing HAN is a senior staff engineer in Zhejiang E-Commerce Bank Co., Ltd., taking charge of Data Intelligence Department. She is a member of CCF (China Computer Federation). Her research interests are in recommender system, searching engine, marketplace and Internet finance.