Combining Intra-Risk and Contagion Risk for Enterprise Bankruptcy Prediction Using Graph Neural Networks

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Abstract—Predicting the bankruptcy risk of small and medium-sized enterprises (SMEs) is an important step for financial institutions when making decisions about loans. Existing studies in both finance and AI research fields, however, tend to only consider either the intra-risk or contagion risk of enterprises, ignoring their interactions and combinatorial effects. This study for the first time considers both types of risk and their joint effects in bankruptcy prediction. Specifically, we first propose an enterprise intra-risk encoder based on statistically significant enterprise risk indicators taken from its basic business information as well as litigation information for its intra-risk learning. Then, we propose an enterprise contagion risk encoder based on enterprise relation information from an enterprise knowledge graph for its contagion risk embedding. In particular, the contagion risk encoder includes both the newly proposed Hyper-Graph Neural Networks (Hyper-GNNs) and Heterogeneous Graph Neural Networks (Heter-GNNs), which can model contagion risk in two different aspects, i.e., common risk factors based on hyperedges and direct diffusion risk from neighbors, respectively. Using these two types of encoders, we design a unified framework to simultaneously capture intra-risk and contagion risk for bankruptcy prediction. To evaluate the model, we collect real-world multi-sources data on SMEs and build a novel benchmark dataset called SMEsD. We provide open access to the dataset, which is expected to further promote research on financial risk analysis. Experiments on SMEsD against twelve state-of-the-art baselines demonstrate the effectiveness of the proposed model for bankruptcy prediction.

Index Terms—Enterprise Bankruptcy Prediction, Intra-Risk, Contagion Risk, Hyper-GNNs, Heterogeneous GNNs

1 INTRODUCTION

Small and medium-sized enterprises (SMEs) contribute up to 40% of gross domestic product (GDP) in emerging economies and provide more than 50% of employment worldwide. Predicting the financial risk of SMEs is of great importance for both government policymakers and financial institutions [1], [2]. Previous studies of enterprise risk in both finance and AI research fields typically either examine enterprises’ internal financial aspects to detect intra-risk (i.e., risks resulting from enterprises’ operations), or they analyze risk diffusion based on simulations [3], [4], [5], [6], [7], [8], [9] to mine contagion risk (i.e., risk from external stakeholders), including upstream and downstream companies and related persons. For simplicity, however, most studies only consider either intra-risk or contagion risk individually, ignoring their interactions and combinatorial effects. Given the heterogeneous multi-source characteristics of intra-risk data and the complexities of contagion risk relations among enterprises, building a framework for enterprise bankruptcy prediction that considers both intra-risk and contagion risk is a non-trivial and challenging task.

To meet this challenge, we propose a novel enterprise bankruptcy prediction method that combines intra-risk with contagion risk. First, we propose an intra-risk encoder that leverages rich features based on enterprises’ basic business information and litigation information to mine intra-risk. After statistically analyzing the correlations between enterprises’ basic intelligence (including basic business attributes and litigation information) and their bankruptcy risk (see Table 1), we successfully select 12 statistically significant indices for intra-risk encoder learning (see Section 2.1 for details about the analysis of statistical significance). Second, we propose an enterprise contagion risk encoder based on enterprise relational information from an enterprise knowledge graph (EKG) to embed contagion risk (also known as “risk momentum spillover effect” [10]). Figure 1 shows a toy example of an EKG, from which we can find that enterprises have two kinds of relations: hyperedges and pair-wise heterogeneous relations (see Section 2.2 for details). Hence, we equip the contagion risk encoder with two submodels—hypergraph neural networks (Hyper-GNNs) and heterogeneous graph neural networks (Heter-GNNs)—to model risk diffusion in the EKG. Specifically, Hyper-GNNs aims to mine hyperedges in the EKG, such as the same industry and the same area, which is beneficial for enterprise risk prediction. During COVID-19, for example, most mask and vaccine manufacturers in the medical industry experienced a boom while the catering industry faced a significant bankruptcy risk. Heter-GNNs, meanwhile, can capture the direct contagion risk...
The statistical significance analysis on the correlation between the enterprises’ basic intelligence (including the enterprise basic attributes, the enterprise litigation information here) and their bankruptcy risk. The symbols ‘***’, ‘**’ and ‘*’ denote the statistical result is significant in 99%, 95% and 90% level, respectively.

| Enterprises intelligence | Significant indices | Correlation analysis | Independent Samples t Test |
|--------------------------|---------------------|----------------------|---------------------------|
|                          |                     | Coefficient         | Polarity                  | Average number of surviving enterprises | Average number of bankrupted enterprises | Significance value of average difference |
| Enterprise Attributes    | Established time    | -.058***            | Negative                  | 156                              | 148                              | .000***                             |
|                          | Registered capital  | -.187***            | Negative                  | 16874                           | 910                              | .016**                              |
|                          | Paid-in capital     | -.159***            | Negative                  | 16264                           | 873                              | .020***                             |
| Lawsuit Cause            | Loan contract dispute | .122***            | Positive                  | 1.80                             | 2.23                             | .032**                              |
|                          | Sales contract dispute | .077***            | Positive                  | .55                              | .80                              | .000***                             |
| Court Level of Lawsuit   | Grassroots people’s court | .086***            | Positive                  | 2.79                             | 3.43                             | .019**                              |
|                          | Intermediate people’s court | -.029**         | Negative                  | .59                              | .43                              | .012**                              |
|                          | Higher people’s court | -.070***            | Negative                  | .05                              | .01                              | .000***                             |
| Verdict                  | Plaintiff winner    | -.076**             | Negative                  | .88                              | .24                              | .000***                             |
|                          | Defendant loser      | .124***             | Positive                  | 1.87                             | 3.12                             | .000***                             |
| Duration Of Action       | Less than two years  | .079***             | Positive                  | 3.23                             | 3.82                             | .059*                               |
|                          | More than two years  | -.086***            | Negative                  | .19                              | .06                              | .000***                             |

Fig. 1. A toy example of enterprise knowledge graph which is extracted from the newly constructed dataset SMEsD.

The contributions of this work are fourfold:

- We conduct exploratory data analysis to demonstrate that the enterprise intelligence (i.e., enterprise basic attributes, litigation information and the EKG) affects bankruptcy risk prediction for SMEs.
- We propose a novel framework for inferring enterprise bankruptcy by considering both intra-risk and contagion risk. To the best of our knowledge, this is the first attempt to consider both risks simultaneously and their joint effects in bankruptcy prediction.
- Under this framework, we utilize an intra-risk encoder to derive intra-risk from an enterprise’s basic intelligence. We propose a new GNNs based contagion risk encoder that includes Hyper-GNNs and Heter-GNNs to calculate contagion risk based on hyperedges and pair-wise heterogeneous relations in the EKG.
- We propose a new benchmark dataset (SMEsD) to evaluate the proposed method, which is also expected to further promote enterprise financial risk analysis. The empirical experiments using our dataset demonstrate that the proposed method can successfully combine enterprise intra-risk and contagion risk for bankruptcy prediction.

2 Exploratory Analysis

In this section, we conduct an exploratory analysis of the relationship between the enterprise intelligence (i.e., enterprise basic attributes and litigation information, and the EKG), and bankruptcy risk. We first give the results for the statistical correlations and Independent Samples t Test results between the basic attributes and the lawsuit features of the enterprises and their bankruptcy status. Then, we introduce a contagion risk analysis of the EKG for bankruptcy prediction.

2. There are several top conference papers that did not provide their datasets for reproduction. Examples include SemiGNN [11] at ICDM 2019; HACUD [12] at AAAI 2019; ST-GNN [13] at IJCAI 2020; AMG-DP [14] at CIKM 2020; TemGNN [15] at SDM 2021; PC-GNN [16] at WWW 2021.

3. The codes and datasets for reproduction are released on GitHub: [https://github.com/shaopengw/ComRisk](https://github.com/shaopengw/ComRisk).
2.1 Statistical Significance Analysis

We collect 11,523 civil lawsuits for 3,976 Chinese SMEs from 2000 to 2021 and the basic attributes of these enterprises. Table 1 summarizes the statistical analysis of the correlations and the Independent Samples t Test between the enterprises’ basic intelligence (i.e., enterprise basic attributes and litigation information; see Definition 1) and their bankruptcy risk. The first part in Table 1 refers to enterprise basic attributes (i.e., established time, registered capital, and paid-in capital). The last four rows in Table 1 concern the most significant features of lawsuits (i.e., lawsuit cause, court level, verdict, and duration of action). We present the analysis results below.

Enterprise Attribute. The first part concerns enterprise basic attributes, including established time (counted by months), registered capital, and paid-in capital (counted by 10,000 yuan). From Table 1, we can find the following:

- All three indicators are significantly negatively correlated with bankruptcy. The indicators of surviving enterprises are significantly higher than those of bankrupted enterprises in the t Test.

This indicates that the longer the established time, the greater the registered capital, and the greater the paid-in capital, the lower the probability of bankruptcy.

Lawsuit Cause. We explore the correlation between lawsuit causes and enterprise bankruptcy. In Table 1, we find that both types of lawsuit causes (i.e., loan contract dispute and sales contract dispute) are significantly correlated with enterprise bankruptcy. Specifically, the correlation coefficient between the number of loan contract disputes and enterprise bankruptcy is 0.122, which is statistically significant at the 99% level. The correlation coefficient between sales contract disputes and enterprise bankruptcy is 0.077, which is also statistically significant at the 99% level. These findings confirm that bankrupted enterprises tend to have more loan contract and sales contract disputes, which is in line with intuition. Meanwhile, we can observe that the average number of loan contract disputes among the surviving enterprises is 1.80, and the number for bankrupted enterprises is 2.23. The difference between the two is significant at the 95% level based on the t Test, which reaffirms the correlation between enterprise bankruptcy and loan contract disputes. We can obtain a similar conclusion from the statistical results for sales contract disputes.

In summary, we find the following:

- The number of loan contract disputes and the number of sales contract disputes are both significantly positively correlated with enterprise bankruptcy.

Court Level of Lawsuit. The court level of a lawsuit is another factor related to enterprise risk. There are four levels of court types (from low to high): grassroots people’s court, intermediate people’s court, higher people’s court and supreme people’s court. Most lawsuits are dealt with by the grassroots people’s court while some involving large underlying assets are brought to intermediate court. If the litigant disagrees with the verdict, it can appeal to a higher court. From Table 1, we can find the following:

- The number of grassroots court lawsuits is significantly positively correlated with enterprise bankruptcy.
- The lawsuit numbers of both intermediate people’s court and higher people’s court are significantly negatively correlated with enterprise bankruptcy.

These findings indicate that bankrupted enterprises tend to have more grassroots court lawsuits and fewer intermediate and higher court lawsuits. This could mean that being involved in a large number of grassroots court lawsuits implies that an enterprise has financial risk. Meanwhile, involvement in many high court lawsuits may reflect an enterprise’s powerful capacity to deal with lawsuits, as well as its larger business scale. The t Test confirm this conclusion.

Verdict. We divide the results of lawsuits into four types according to litigant status and the verdict: plaintiff winner, plaintiff loser, defendant winner, and defendant loser. From Table 1, we can observe the following:

- Enterprises that are plaintiff winners are less likely to go bankrupt (i.e., significantly negative correlation).
- Enterprises that are defendant losers are more prone to bankruptcy (i.e., significantly positive correlation).

The correlation coefficients of the two types of verdicts are both significant at the 99% level, which confirms the importance of lawsuit results. The reason is that being a plaintiff winner in a lawsuit is good news for an enterprise, and being a defendant indicates risk. We can draw the same conclusion from the difference between the average number of the two types of lawsuit results for bankrupt and surviving enterprises in the t Test.

Duration of Action. Referring to [17], we divide duration of action (DOA) into two types: less than two years and more than two years. From Table 1, we can find the following:

- The correlation between the number of lawsuits in the last two years and enterprise bankruptcy is significantly positive.
- The correlation between the number of lawsuits more than two years ago and enterprise bankruptcy is significantly negative.

These findings indicate that bankrupted enterprises tend to have had more lawsuits in the two years prior to bankruptcy. The more lawsuits, the greater the direct risk for an enterprise, especially in the case of lawsuits in the last two years. Meanwhile, having been involved in a large number of lawsuits more than two years ago implies that an enterprise has experienced many disputes but has survived. This indicates that the enterprise has a large business scale and is strong enough to face various challenges.

2.2 Contagion-Risk Analysis

The contagion effect has been used to study stock movement prediction [18], in which stock fluctuations are partly affected by related stocks. In this study, contagion risk means that the risk generated by an enterprise tends to diffuse through the EKG to neighboring enterprises, which is ubiquitous in real market circumstances [13], [19], [20], [21]. Figure 1 shows an example of the EKG extracted from our newly generated dataset (SMEsD), from which we can find that enterprises have two types of relations: hyperedges and pair-wise heterogeneous relations. (i) There are three types of hyperedges in the EKG (see Definition 2): industry, area, and stakeholder, colored red, yellow, and green, respectively. For example, enterprise A, enterprise D, and enterprise E are in the same city. Then, they are influenced by the same regional policies (e.g., tax administration and economic policy) and face similar regional risks. Hence, we propose a Hyper-GNN to model such contagion risk. (ii) There are five types of pair-wise heterogeneous relations among enterprises and persons (see...
3 Problem Formulation

Definition 1. Enterprise basic intelligence. Enterprise basic intelligence consists of two parts (i.e., the enterprise basic attributes and the enterprise litigation information as is shown in Table 7), which can be formulated as |A| = (B, J). B = \{b_1, b_2, ..., b_i, ..., b_N\} denotes set of enterprise basic business information. N denotes the number of enterprises. b_i = (ct_i, rc_i, pc_i) denotes attributes for enterprise i, including established time, registered capital and paid-in capital. J = \{J_1, J_2, ..., J_i, ..., J_K\} denotes enterprise litigation information of enterprises. j_i = \{j_i, j_i^2, ..., j_i^k\} denotes the number of lawsuits for enterprise i. j_i^k = (c_i^k, f_i^k, v_i^k, k_i^k) denotes a specific lawsuit k related to enterprise i, including lawsuit cause, court level of lawsuit, verdict and time interval of action.

Definition 2. Enterprise hyper-graph. An enterprise hypergraph can be defined as \( G_{hyper} = (V_e, E, \Theta_{hyper}) \). Here, \( V_e \) denotes the set of enterprise nodes, E = \{h_1, h_2, ..., h_i\} denotes hyperedge set. \( \Theta_{hyper} = \{\Omega_1, \Omega_2, ..., \Omega_M\} \) denotes hyperedge type set, and \( |\Theta_{hyper}| > 1 \) here. Hyperedge type map function \( \psi(h_p) \in \Theta_{hyper} \). The relationship between enterprise nodes can be represented by an incidence matrix \( H \in \mathbb{R}^{|V| \times |E|} \) with elements defined as:

\[
H(v, h_p) = \begin{cases} 
1, & \text{if } v \in h_p \\
0, & \text{otherwise}
\end{cases}
\]

\( v \in V_e \) denotes an enterprise node, and \( h_p \in E \) denotes a hyperedge.

Definition 3. Enterprise heterogeneous-graph. An enterprise heterogeneous graph is defined as a connected graph \( G_{hete} = (V, \mathcal{L}, \mathcal{T}, R, W) \). V denotes the set of all nodes. \( \mathcal{L} \) denotes a link set. They are associated with two functions: (i) a node type mapping function \( \phi : V \rightarrow \mathcal{T}, \mathcal{V} = \{V_e, \mathcal{V}_p\}, \mathcal{V}_e, \mathcal{V}_p \) denote the node set of enterprises and persons, respectively. \( \mathcal{V}_e \cap \mathcal{V}_p = \emptyset \). Each node \( v \in V \) belongs to one particular type in node type set \( \mathcal{T} \): \( \phi(v) \in \mathcal{T} \). (ii) a link class mapping function \( \psi : \mathcal{L} \rightarrow R \). W denotes edge weights.

Problem 1. Enterprise bankruptcy prediction. Given an enterprise multi-source data, which consists of enterprise basic intelligence \( \mathcal{A} \), an enterprise heterogeneous hypergraph \( G_{hyper} \) and an enterprise heterogeneous graph \( G_{hete} \), we aim to determine enterprise risk, considering both intra-risk and contagion risk. Based on enterprises’ representations, we conduct bankruptcy prediction task, which can be treated as a binary classification problem.

4 Related Work

4.1 Enterprise Risk Analysis

Enterprise Intra-Risk In traditional, enterprise risk analysis methods mainly consider financial indicators, such as profitability, operating efficiency, and solvency, using multivariate discriminant analyses or machine learning methods, such as SVM and decision trees. For example, Erdogan et al. propose an ensemble method utilizing SVMs as base classifiers for commercial bank bankruptcy. Many other studies use neural networks to improve prediction accuracy. Hosaka et al. transform financial ratios into images using convolutional networks for bankruptcy prediction. Recently, many studies have focused on using text information, such as financial reports and conference calls, to mine enterprise intrarisk. For instance, Borochin et al. find that the tone of conference calls is negatively related to firm value uncertainty in the equity options market. Li et al. develop a large-scale multimodal dataset called MAEC, and their experiments demonstrate the efficiency of the dataset for volatility forecasting. Liu et al. construct six pretraining tasks trained on both general and financial domain corpora, enabling them to capture financial-specific semantic information.

However, SMEs usually lack normal financial reports as well as public conference calls, which poses challenges for the analysis of SMEs. On the other hand, there are abundant risk sources such as relevant lawsuits, which are known to be significantly related to enterprise credit risk, which have not been well utilized in previous works.

Enterprise Contagion-Risk Enterprise contagion-risk is also an important part of risk analysis since no enterprise is completely independent of other companies. Some financial studies propose using interconnections between firms or assets for risk analysis. Eisenberg et al. propose, for example, to take interconnections among firms into consideration to study obligation-clearing mechanisms. Elsinger et al. propose assessing systemic financial stability using a network model of interbank loans. Acemoglu et al. provide a framework for studying the relationship between financial network architecture and the likelihood of systemic failure considering contagion risk and find that financial contagion exhibits a form of phase transition as interbank connections increase.

Most previous studies, however, explore the effects of contagion risk using simulations, which cannot be applied to real scenarios.

4.2 Graph Neural Networks

Graph neural networks (GNNs) use deep neural networks to deal with graph representation learning. They have proven to be successful for various tasks on graphs, such as node classification, link prediction, and community detection. GNNs also contribute to traditional scenarios, such as recommendation systems, natural language processing and computer vision. For more surveys of GNNs.

Enterprise interconnections naturally form a heterogeneous graph, consisting of enterprise nodes, person nodes, and the connections among them. In the fintech field, some studies use GNNs to model various risks. For example, SemiGNN involves using labeled and unlabeled multiview data for fraud detection. Hu et al. model various relations, objects, the rich attributes of nodes and edges for loan default detection. CCR-GNN is proposed to solve the problem of corporate credit rating. Yang et al. examine supply chain relationships and conduct lift prediction on a collected supply chain dataset. Kosash et al. pose the supply chain visibility problem as a link prediction...
problem via GNNs. Pan et al. [49] used a triple-layer attention network for bankruptcy prediction considering different metapath based neighbors.

Hypergraphs have shown a strong capacity to model higher-order relationships, which have been used in many areas, such as social recommendation [50], [51] and computer vision [52], [53]. With regard to enterprise risk modeling, there is a large number of hyperedges among enterprises and related persons, which is suitable for using hypergraphs. Few studies, however, have applied hypergraph neural networks in this area.

As discussed previously, few researchers have considered both intra-risk and contagion risk simultaneously in relation to bankruptcy prediction. Further, most fail to sufficiently mine risk information because of complex risk sources and relationships. Meanwhile, few studies provide open access data for other researchers, which restricts the development of risk analysis research in areas such as bankruptcy prediction and default prediction.

5 Methodology

In this section, we introduce the overall architecture of the proposed method, as shown in Figure 2. The proposed model consists of three main parts: (I) the enterprise intrarisk encoder, which uses statistically significant enterprise features (Table I); (II) Enterprise Contagion Risk Encoder, which consists of two submodules: (a) Hyper-GNNs, using enterprise hypergraphs, and (b) Heter-GNNs, using enterprise heterogeneous graphs; and (c) Combining intra- and contagion risk. (III) Enterprise Bankruptcy Prediction. Different from previous work, we take advantage of a hierarchical mechanism for both Hyper-GNNs and Heter-GNNs to utilize complex heterogeneous hyperedges and relationships. We provide the details below.

5.1 Enterprise Intra-Risk Encoder

The enterprise intra-risk encoder aims to learn enterprise self-risk embedding using enterprise basic intelligence (i.e., enterprise basic attributes and enterprise litigation information), which is formally given in Definition I.

As Figure 3 first, for each enterprise node \( v_i \in V_e \), we use \( b_i \in \mathbb{R}^d \) in Definition I as the basic attribute features. Second, the lawsuit event \( j^k_i \) of enterprise \( i \) contains four significance attributes (i.e., lawsuit cause, court level, verdict, and DOA), as described in Section 2.1. For the first three attributes, we map each into latent spaces and then concatenate them to obtain lawsuit representation \( s^k_i \in \mathbb{R}^d \). Referring to [54], we use a time decay function \( \text{Decayer} \) to weight each lawsuit representation to make better use of time information in lawsuit events. Specifically, we calculate the time interval \( \Delta^k_i \) between the time of occurrence of each lawsuit and the enterprise’s observation time. For bankrupted enterprises, the observation time is set as the time of bankruptcy while for surviving enterprises, it is set as the present.

\[
g(\Delta^k_i) = \frac{1}{1 + w \cdot \Delta^k_i},
\]
Because lawsuits in the last two years play an important role in enterprise risk prediction [17], we assign a lower \( w \) when performing time weight decay for lawsuits in the last two years.

Then, we aggregate lawsuit information from different time periods as follow:

\[
h_i^r = \sum_{k \in K_i} W_{risk} \cdot g(\Delta_i^k) \cdot s_i^k, \tag{3}
\]

where \( W_{risk} \in \mathbb{R}^{d \times d} \) is a trainable matrix, \( h_i^r \) is the aggregated lawsuit information of company \( i \).

We also generate a pre-trained embedding \( u_i \in \mathbb{R}^d \) for enterprise \( i \) as a supplement embedding. Finally, we concatenate the basic attribution features, litigation embedding, and supplement embedding and project it into a new latent space as follow:

\[
h_i = W_i \cdot [b_i || h_i^r || u_i]. \tag{4}
\]

\( h_i \) denotes the output of intra-risk representation of the enterprise \( i \). \( || \) denotes the concatenation operation. \( W_i \in \mathbb{R}^{(d_1 + d_2 + d_3) \times d} \) is a trainable matrix.

### 5.2 Enterprise Contagion Risk Encoder

#### 5.2.1 Hyper-Graph Neural Networks

Hypergraphs play an important role in bankruptcy prediction, as the hyperedges reflect common factors that enterprises face. Thus, it is natural to utilize hypergraphs to capture common risk information, such as industry development recession, regional economic policy changes, and guarantee risk caused by the same stakeholders.

![Fig. 4. Hyper-Graph Neural Networks.](image)

As shown in Figure 4, because different types of hyperedges contribute to node representation at different levels, we assign different weights to them when aggregating node representations. Specifically, following Feng et al. [55], we first calculate the hypergraph convolution module as follow:

\[
\Theta_{\Omega_m} = D_v^{-1/2} H_{\Omega_m} W D_v^{-1/2}, \tag{5}
\]

where \( \Theta_{\Omega_m} \in \mathbb{R}^{|V_e| \times |V_e|} \) denotes the convolution module. \( D_v \) is the enterprise node degree matrix. \( H_{\Omega_m} \) denotes the incident matrix of the hypergraph type \( \Omega_m \). \( W \) is the node weight matrix. We set it as an identity matrix, which means all weights are equal. \( D_v \) denotes the hyperedge degree matrix. Afterwards, we conduct hypergraph convolution under the hypergraph type \( \Omega_m \) as follow:

\[
\hat{H}_{\Omega_m}^{l+1} = (I - \Theta_{\Omega_m}) W_{hp} \hat{H}_{\Omega_m}^l, \tag{6}
\]

where \( \hat{H}_{\Omega_m}^{l+1} \) denotes the learned representations under the hypergraph type \( \Omega_m \) of layer \( l + 1 \), \( I - \Theta_{\Omega_m} \) denotes the hypergraph

laplacian, \( W_{hp} \in \mathbb{R}^{d \times d'} \) is a trainable matrix, which is shared for different types of hypergraphs. Then we aggregate the different types of hypergraph convolution representations as follow:

\[
z_i = \sum_{\Omega_m \in \mathcal{T}_{hyper}} e^{\Omega_m} \cdot \hat{h}_{i\Omega_m}^l, \tag{7}
\]

where \( z_i \in \mathbb{R}^{d'} \) is the learned hypergraph comprehensive representation of enterprise \( i \), and \( e^{\Omega_m} \) is a trainable parameter, which denotes the importance of hypergraph \( \Omega_m \) for all enterprise nodes.

#### 5.2.2 Heterogeneous Graph Neural Networks

We propose the Heter-GNNs to sufficiently make use of multiplex interactions among enterprises and persons. Specifically, we first aggregate entity level information and then relationship level in a hierarchical mechanism as shown in Figure 5.

![Fig. 5. Heterogeneous Graph Neural Networks.](image)

We initialize the person node representations the same as for enterprises in Section 5.2. Then we perform transformation based on node type to project enterprise node and person representation to same latent space as follow:

\[
h_i' = \text{Norm}(W_{\phi(v_i)} h_i), \tag{8}
\]

where \( W_{\phi(v_i)} \in \mathbb{R}^{d \times d'} \) is a node type specific trainable weight matrix. \( h_i \in \mathbb{R}^d \) and \( h_i' \in \mathbb{R}^{d'} \) are the original and transformed node representations, respectively. \( \text{Norm} \) denotesBatch Normalization operation [56]. Then we conduct entity level aggregation. For weighted edges, such as \( \text{holder}_{	ext{investor}} \), we directly set the ratio of contribution capital as the edge weight. For unweighted relations, we use the attention mechanism to assign weights for node \( v_i \)’s neighbors’ representation as follows:

\[
e^{ij \phi_k} = \text{Att}_{entity}(h_i', h_j', \Phi_k) = \text{LeakyRelu}(W_{\phi_k} \cdot [h_i' || h_j']), \tag{9}
\]

where \( e^{ij \phi_k} \) is the learned importance of node \( i \)’s neighbor \( j \) under relationship \( \Phi_k \). \( W_{\phi_k} \in \mathbb{R}^{2d' \times d'} \) is a trainable matrix, and \( \text{LeakyRelu} \) is an activation function. To make the weights comparable, we utilize \( \text{Softmax} \) function to normalize weights across all choices of \( j \) as follows:

\[
e^{ij \phi_k} = \text{Softmax}_{j}(e^{ij \phi_k}) = \frac{\exp(e^{ij \phi_k})}{\sum_{v_j \in N^k(v_i)} \exp(e^{ij \phi_k})}, \tag{10}
\]
\[ r_i^{\Phi_k} = \sum_{v_j \in \mathcal{N}_v^k} \alpha_{ijm} \cdot h_{jm}^i, \quad (11) \]

where \( r_i^{\Phi_k} \) is the m-th element of the aggregated \( \Phi_k \) unweighted relationship representation for node \( v_i \), \( \alpha_{ijm} \) is the m-th dimension of the normalized importance of node \( j \) related to node \( i \) under the unweighted relationship \( \Phi_k \), \( \mathcal{N}_v^k \) denotes node \( i \)'s neighbors under unweighted relationship \( \Phi_k \). For weighted edges, we implement node level aggregation as follows:

\[ h_{ij}^{\Phi_k} = \text{Softmax}_j(w_{ij}^{\Phi_k}) = \frac{\exp(w_{ij}^{\Phi_k})}{\sum_{v_p \in \mathcal{N}_v^k} \exp(w_{ip}^{\Phi_k})}, \quad (12) \]

\[ r_i^{\Phi_k} = \sum_{v_j \in \mathcal{N}_v^k} h_{ij}^{\Phi_k} \cdot W_2^{\Phi_k} h_j, \quad (13) \]

where \( h_{ij}^{\Phi_k} \) denotes the normalized importance that node \( j \) has for node \( i \) under weighted relation, and \( w_{ij}^{\Phi_k} \) denotes original edge weight between node \( i \) and node \( j \) (e.g., such as contribution capital). \( W_2^{\Phi_k} \in \mathbb{R}^{d \times d'} \) is a trainable matrix, \( r_i^{\Phi_k} \) denotes the learned aggregated representation of node \( i \)'s neighbors under the weighted relationship \( \Phi_k \).

To fully capture the risk information implied in different relationships, we use transformer based attention mechanism:

\[ g_{ik} = k^T q_i \cdot \frac{\mu^{\Phi_k}}{\sqrt{d}}, \quad q_i = W_Q^{\Phi_k} h_i + b_Q^{\Phi_k}, \quad (14) \]

\[ k_i = W_K^{\Phi_k} r_i^{\Phi_k} + b_K^{\Phi_k}, \]

where \( g_{ik} \) denotes the relationship level importance that relation \( \Phi_k \) has for node \( i \), and \( W_Q^{\Phi_k}, W_K^{\Phi_k} \in \mathbb{R}^{d \times d'} \) are trainable matrices in relationship \( \Phi_k \), \( b_Q^{\Phi_k}, b_K^{\Phi_k} \in \mathbb{R}^{d'} \) are trainable parameters in relationship \( \Phi_k \), \( \mu^{\Phi_k} \) is a trainable parameter used to adjust the scale of learned importance, which is relationship type specific. Similarly, we utilize the Softmax function to normalize learned attention and aggregate relationship level representations as follows:

\[ \beta_{ik} = \text{Softmax}_k(g_{ik}) = \frac{\exp(g_{ik})}{\sum_{\phi_j \in \mathcal{R}} \exp(g_{ij})}, \quad (15) \]

\[ \bar{h}_i = \sum_{\phi_j \in \mathcal{R}} \beta_{ij} \cdot (W_V r_j^{\phi} + b_V). \quad (16) \]

where \( \beta_{ik} \) denotes the normalized importance of relationship \( \Phi_k \) for node \( i \), \( W_V \in \mathbb{R}^{d \times d'} \) and \( b_V \in \times \mathbb{R}^{d'} \) are trainable parameters. \( \bar{h}_i \) is the learned aggregated risk information for node \( i \). Next, we use the residual connection to get the final risk information of the heterogeneous graph as follow:

\[ \bar{z}_i = \eta \sigma(h_i') + \bar{h}_i, \quad (17) \]

where \( \eta \) is the learned weight to balance the aggregated risk information and nodes’ initial risk information, \( \sigma \) is the GELU activation function and \( \bar{z}_i \) is the final risk information of node \( i \).

### 5.2.3 Combining Intra- and Contagion Risk

We sum the propagated risk from the Hyper-GNNs and Heter-GNNs to get the contagion-risk as follow:

\[ z_i^{\text{cont}} = W_{\text{cont}} \cdot (\bar{z}_i + \bar{z}_i), \quad (18) \]

where \( W_{\text{cont}} \in \mathbb{R}^{d \times d'} \) is a trainable matrix and \( z_i^{\text{cont}} \) is the learned contagion risk.

Then, we combine the node intra-risk and contagion-risk information as follow:

\[ \bar{z}_i = \lambda \sigma(z_i^{\text{cont}}) + (1 - \lambda) \text{MLP}(\bar{h}_i). \quad (19) \]

where \( \bar{z}_i \) is the final representation of node \( i \), and \( \lambda \) is a trainable parameter to balance contagion risk and intra-risk. \( \sigma \) is an activation function, we choose GELU here. MLP is a two-layer multilayer perception with the ReLU activation function in it.

### 5.3 Optimization

We sum the learned representations of Hyper-GNNs and Heter-GNNs and utilize a fully connected layer to transform learned node representations for bankruptcy prediction, as in Figure 2 (III).

\[ \bar{y}_i = \text{Softmax} \left( W_p \bar{z}_i + b_p \right), \quad (20) \]

where \( W_p \) is a trainable matrix and \( b_p \) is the bias vector. Finally we train the model by minimizing cross-entropy loss:

\[ \mathcal{L} = - \sum_{i \in \mathcal{Y}_L} y_i \log(\bar{y}_i). \quad (21) \]

where \( \mathcal{Y}_L \) is the set of labeled nodes, \( y_i \) and \( \bar{y}_i \) are the ground truth and the predicted bankruptcy probability for node \( i \), respectively.

### 6 EXPERIMENTS

#### 6.1 Experimental Settings

##### 6.1.1 Datasets

To examine the performance of the proposed model for bankruptcy prediction, we manually collect and preprocess a real-world SME dataset, which we call SMEsD. To the best of our knowledge, this dataset is the largest multimode bankruptcy prediction dataset, and it contains abundant multidimensional information. SMEsD consists of 3,976 SMEs and related persons in China from 2014 to 2021, constituting a complex EKG. All enterprises are associated with their basic business information and lawsuit events spanning 2000–2021. Specifically, enterprise business information includes registered capital, paid-in capital, and established time. Each lawsuit consists of the associated plaintiff, defendant, subjects, court level, result, and timestamp.

Table 2 presents the statistics of the SMEsD. The dataset contains two types of nodes: enterprise and person. For the enterprise heterogeneous graph, there are five types of relationships between enterprises and persons. The holder_investor relationship is weighted by the contribution capital, and the other edges are unweighted. For the hypergraph, there are three types of edges: industry, area, and stakeholder. We split SMEsD into a training set, validation set, and testing set across the bankruptcy time.
6.1.2 Baselines

To measure the effectiveness of our method, we compare the proposed model with four types of state-of-the-art (SOTA) methods: (1) the conventional machine learning based method that only considers enterprise lawsuit information including lawsuit attribute frequency and basic business information; (2) hypergraph neural networks based methods that take high-order relationships among enterprises into consideration; (3) homogeneous GNNs based methods that use abundant connections among enterprises, which can capture contagion risk; and (4) heterogeneous GNNs based methods that can distinguish complex relationships in an EKG.

**Conventional Machine Learning (ML) Based Methods**

- Logistic Regression (LR) [59]: a well known method applied in machine learning, social science and biometrics when explained variables are discrete.
- Support Vector Machine (SVM) [60]: a model utilized support vectors to divide vector spaces into different classes.
- Gradient Boosting Decision Tree (GBDT) [61]: a classic tree classification model of conventional machine learning.

**Hypergraph Neural Networks (HyperG) Based Methods**

- Hypergraph Neural Networks (HGNN) [55]: a model proposed to utilize high-order relationship information in graphs.
- Hypergraph Wavelet Neural Network (HWNN) [62]: a newly proposed model which makes use of wavelet basis instead of Fourier basis to perform localized hypergraph convolution.

**Homogeneous GNNs (HomoG) Based Methods**

- Graph Convolutional Networks (GCN) [63]: a popular model which averages neighbors’ information during the message passing process.
- Graph Attention Networks (GAT) [67]: a recent model which takes attention mechanism to align different weights to neighbors during the information aggregating process.

**Heterogeneous GNNs (HeteG) Based Methods**

- Relational Graph Convolutional Networks (RGCN) [64]: an advanced extension of GCN, which takes relationship information into consideration by giving different weights for different relationships.
- Heterogeneous Graph Attention Network (HAN) [66]: one of the earliest models to implement hierarchical attention based on the metaphet relationships in graph neural networks.
- hypergraph attention based (HAT) [68]: a SOTA model which conducts triple-level attention in SMEs bankruptcy prediction.

6.2 Experiment Details

For all of the baseline methods, we calculate enterprise risk information by counting the number of lawsuit attributes and combining them with basic enterprise business attributes as enterprise risk representations. We use random initialization based on standard normal distribution to assign initial representations for enterprises and persons when implementing GNN-based methods. We choose Metapath2vec [69] as the pre-trained model for COMRISK to generate the supplement embeddings. We implement COMRISK and baselines with PyTorch and PyTorch Geometric (PyG). We refer to THU-HyperG [70] to construct the hypergraphs. We implement baselines based on official codes with fine-tuning parameters, including hidden dimension, layer number, and multihedead number, to obtain better performance. All neural network–based models are trained with the Adam optimizer [71] and the Cosine Annealing Learning Rate Scheduler [72]. We set input dimension 16 and output dimension 12 for each model. We run all methods for 500 epochs and update the models considering the improvement of the two comprehensive indicators on the validation dataset (i.e., the accuracy and F1 score to alleviate the overfitting problem). We report the results of all methods on the testing dataset.

6.3 Experimental Results and Analysis

Table 3 shows the evaluation results against 12 SOTA baselines. We can see that the proposed method outperforms all baselines for enterprise bankruptcy prediction in terms of all of the comprehensive metrics on our newly generated dataset (SMEsD). Specifically, COMRISK achieves SOTA performance with improvements of 4.68%, 1.38%, and 9.23% for accuracy, F1, and AUC scores, respectively. This confirms the ability of our method to use both intrarisk and contagion risk for bankruptcy prediction.

**Major Analysis.** (1) We observe that the SVM achieves good performance for recall. This is because lawsuit information and basic enterprise information are highly correlated with enterprise bankruptcy. However, the SVM has poor performance on other comprehensive metrics because of overfitting. (2) We can observe that all graph based models, including hypergraph neural networks and heterogeneous graph neural networks, perform better on most metrics than machine learning methods. This demonstrates the superiority of using contagion risk for enterprise bankruptcy prediction. (3) We also find that HWNN performs better than HGNN because it considers different types of hyperedges; this demonstrates the necessity of considering hypergraph heterogeneity. (4)
| Models               | Accuracy | Precision | Recall | F1    | AUC    |
|---------------------|----------|-----------|--------|-------|--------|
| ML                  | 0.6091   | 0.6161    | 0.7547 | 0.7144| 0.5812 |
| SVM (1999 [59])     | 0.6314   | 0.6412    | 0.8836 | 0.7564| 0.5256 |
| GBDT (2000 [60])    | 0.6456   | 0.7449    | 0.8887 | 0.7157| 0.6843 |
| HomoG               | 0.6619   | 0.6792    | 0.9057 | 0.7763| 0.7099 |
| GCN (2017 [61])     | 0.6802   | 0.6998    | 0.8686 | 0.7822| 0.6251 |
| HeterG              | 0.6848   | 0.6941    | 0.9277 | 0.7941| 0.6433 |
| HGNN (2019 [62])    | 0.6640   | 0.7029    | 0.8333 | 0.7636| 0.6395 |
| RGCN (2018 [64])    | 0.6965   | 0.7446    | 0.8505 | 0.7746| 0.6857 |
| HAN (2019 [65])     | 0.7332   | 0.7429    | 0.8994 | 0.8137| 0.7331 |
| ie-HGCN (2021 [66])| 0.7270   | 0.7521    | 0.8491 | 0.7976| 0.7560 |
| HAT (2021 [67])     | 0.7312   | 0.7435    | 0.8931 | 0.8114| 0.7006 |
| Loss-weighted ComRisk | 0.7739   | 0.7820    | 0.9025 | 0.8380| 0.8256 |
| ComRisk             | 0.7800   | 0.8409    | 0.8145 | 0.8275| 0.8483 |

In addition, we find that the two SOTA HeterG baseline models (i.e., ie-HGCN and HAN) show better performance than ML and HomoG models, which confirms the ability of heterogeneous graphs to capture contagion risk.

**Credit Scenario Analysis.** Enterprise bankruptcy prediction can be applied to the credit scenario. It is important to support SMEs in this regard since they contribute a great deal to the economy. In the past, banks preferred not to give loans to SMEs since the banks usually did not have reliable access to SMEs’ risk levels, resulting in high recall scores in loan decisions. By contrast, precision is a better indicator that can help banks exclude high-risk enterprises and offer more loans to SMEs while avoiding losses. We can see in Table 3 that the proposed model ComRisk achieves an 8.88% gain over the SOTA baseline model, which can benefit both loan decision-makers and SMEs. Meanwhile, to promote the recall score, we propose LOSS-WEIGHTED ComRisk, which assigns more weight for bankrupt enterprises’ losses during the training process. We can also see in Table 3 that LOSS-WEIGHTED ComRisk achieves comparable performance in recall and maintains excellent performance in other metrics at same time.

**6.4 Ablation Study**

We conduct an ablation experiment to evaluate the effectiveness of different components in the proposed model ComRisk. The three ablated variants are as follows: (1) **ComRisk w/o Intra-Risk**, which deletes the inner risk encoder; (2) **ComRisk w/o Hyper-GNNs**, which removes the hierarchical hypergraph encoder; and (3) **ComRisk w/o Heter-GNNs**, which deletes the hierarchical risk encoder module. Figure 6 shows the results. We can see that removing either the heterogeneous graph, hypergraph, or risk encoder leads to performance degeneration, which demonstrates the effectiveness of the three modules. Specifically, the proposed model ComRisk outperforms **ComRisk w/o Intra-Risk**, which confirms the effectiveness of lawsuit information for bankruptcy prediction. Meanwhile, **ComRisk w/o Hyper-GNNs** has the worst performance among the three ablated variants, which verifies the importance of intrarisk information. Thus, we highlight the design of capturing lawsuit risk information. Compared with **ComRisk w/o Hyper-GNNs**, the proposed model ComRisk also achieves better performance, which demonstrates the contribution of hypergraphs. This is because enterprises in the same industry, in the same area, or with same stakeholders usually face similar external risks (e.g., industry development recession, regional economic policy changes, and guarantee risks), which can be detected by hypergraphs. For **ComRisk w/o Heter-GNNs**, we find that performance also decreases, which confirms that utilizing complex heterogeneous relationships in an EKG can strengthen the capacity of the model.

**6.5 Variant Analysis**

We conduct a variant analysis of ComRisk to show the effectiveness of its architecture. (1) **ComRisk-Frequency** replaces the proposed inner risk encoder with the frequency of lawsuit attributes with regard to each enterprise; (2) **Hyper-GNNs-HGNN** replaces the hierarchical hypergraph encoder with HGNN; and (3) **Heter-GNNs-RGCN** uses RGCN rather than the proposed hierarchical risk encoder. Figure 7 shows the results. We can see that the proposed ComRisk achieves the best performance compared to all variants. Specifically, ComRisk performs better than Risk-Frequency, which again demonstrates the risk-representation capacity of the inner risk encoder. This is because our model not only uses lawsuit risk information in terms of frequency but also considers the time interval related to each lawsuit, which is shown to be significantly correlated with enterprise bankruptcy in Table 4. Compared with Hyper-HGNN, the proposed model ComRisk also performs better because it can distinguish different types of hyperedges and assign different importance weights for the learned representations. We also observe that replacing the hierarchical risk encoder with RGCN lowers performance, from which we can conclude that the proposed hierarchical risk encoder can better capture the contagion risk embedded in complex relationships.
6.6 Parameter Analysis

We examine the effects of the two critical hyper-parameters (i.e., the output dimension and lawsuit risk information dimension in ComRISK), the default dimensions of which are 12 and 20, respectively.

**Impact of input dimension.** As shown in Figure 8(a), performance first increases with the dimension increasing before 12 and then falls with the dimension increasing. This could be because a model with a too-low dimension fails to represent abundant node information. Meanwhile, a high dimension produces too much noisy information and thus restricts the capacity of the model (ComRISK).

**Impact of lawsuit risk information dimension.** We can see in Figure 8(b) that model performance first increases and reaches its peak at 20 and then decreases with the dimension rising. This is mainly because the number of total lawsuit attributes in the SMEsD dataset is 20; lower and higher lawsuit risk dimensions both lead to a decrease in performance.

7 Conclusion

In this study, we propose modeling enterprise bankruptcy risk by combining intrarisk and contagion risk. In this framework, we propose a novel method that includes an intrarisk encoder and GNNs based contagion risk encoder. Specifically, the intrarisk encoder can capture enterprise intrarisk using statistically correlated indicators derived from basic business information and litigation information. The contagion risk encoder consists of hypergraph neural networks and heterogeneous graph neural networks, which aim to model contagion risk in the two aspects of hyperedge and complex heterogeneous relationships among EKGs, respectively. To evaluate the proposed model, we collect multisource SME data and build a new dataset, SMEsD. The experimental results demonstrate the superiority of the proposed method. The dataset is expected to become a significant benchmark dataset for SME bankruptcy prediction while further promoting research on financial risk.

Acknowledgments

The authors would like to thank all anonymous reviewers in advance. This research has been partially supported by grants from the National Natural Science Foundation of China under Grant No. 71725001, 71910107002, 61906159, 62176014, U1836206, 71671141, 71873108, 62072379, the State key R & D Program of China under Grant No. 2020YFC0832702, the major project of the National Social Science Foundation of China under Grant No. 19ZDA092, the Financial Intelligence and Engineering Key Laboratory of Sichuan Province and the Fundamental Research Funds for the Central Universities under Grant No. JBK2207004.

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