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Network based Enterprise Profiling with Semi-Supervised Learning

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ABSTRACT

Enterprise evaluation provides indicators such as ratings and scores by analyzing the characteristics and capabilities of enterprises. The business performance, the level of credit risk, and the economic value of technology are quantitatively evaluated. Although the existing methods are well established, they need improvement in three aspects: fragmentation of information, interpretability of results, and objectivity of evaluation. First, existing methods selectively utilizes the information according to its own purpose. Second, it is hard for those results to understand the rationale of evaluation and the characteristics of enterprise. Third, unofficial information such as personal opinions or profit structures are included in the evaluation. Motivated by the limitations, we propose a machine learning-based enterprise evaluation method consisting of diversified quantification and semi-supervised learning. By quantifying various information, the analysis for identifying enterprise characteristics is primarily performed, and the results are derived as several remarkable features to improve interpretability. Then, by constructing the network, enterprises have compared each other, and they are objectively evaluated by label propagation on the enterprise network. The output is measured as a score, and later its distribution is binned into five grades to improve practicality and usefulness. The proposed method was applied to the dataset of 27,790 enterprises with 113 variables about financial and R&D information. The results show clear identification of enterprise characteristics with the high accuracy of evaluation.

1. Introduction

Enterprise evaluation provides indicators such as ratings and scores by analyzing the characteristics and capabilities of enterprises (Bao, Lianju, & Yue, 2019; Henrique, Sobreiro, & Kimura, 2019; Zhu, Ma, Wang, & Chen, 2017). These indicators are used as a yardstick for decision-making in a variety of situations, including fund investment, loan review, IPO or M&A evaluation, and government business selection (Jang, 2019; Kumar & Ravi, 2007; Liao & Ho, 2010; Qiu, Sallak, Schön, & Ming, 2018). Traditionally, evaluation methods had relied on surveys or expert advice. However, these qualitative methods fall short of the growing number of enterprises and the scope of the investigation is limited. As the solution to this, quantitative methods have emerged that allow efficient evaluation by saving time and cost.

There are three representative quantitative methods for enterprise evaluation: credit rating, economic value added, and technology valuation (Bequé & Lessmann, 2017; Stern, Stewart III, & Chew, 1995). First, credit rating is an index that indicates the level of credit risk, such as default, reflecting the finance of enterprises (Bequé & Lessmann, 2017). Credit rating agencies calculate ratings which are mainly subdivided into 10 grades, from AAA to D, by analyzing the financial statement and the enterprise condition. The financial statement denotes the profitability and liquidity, and the enterprise condition represents the reliability and industry prospect. Second, economic value added (EVA) is an index that evaluates the business performance of enterprises (Hahn & Kuhn, 2012; Stern, 2004; Stern, Stern, Shiely, Ross, & Ross, 2001). EVA indicates how much the enterprise value has been created by production and sales beyond the cost of capital, which includes not only debt capital

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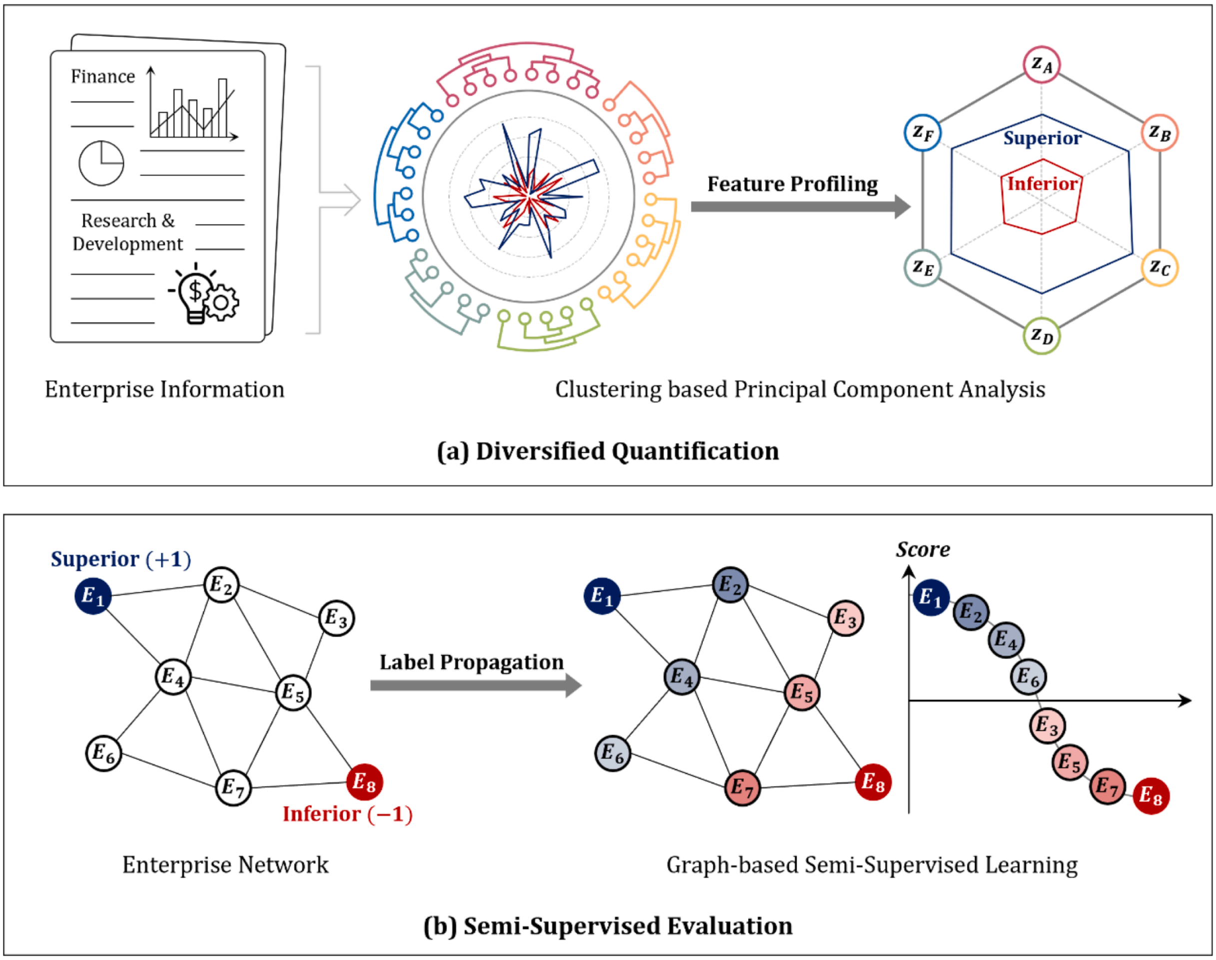


Fig. 1. Overview of Enterprise Profiler. (a) Depicts the process of diversified quantification. This process extracts comprehensive information of enterprises as several key features. (b) Shows the process of semi-supervised evaluation. Semi-supervised evaluation constructs the enterprise network using enterprise features, and therefrom, the evaluation is performed by applying graph-based semi-supervised learning. Consequently, the results are derived so that the evaluation scores of enterprises with similar features are also similar.

but also shareholder capital (Lokanandha Reddy & Reddy, 2006; Qi, 2011). This index is the revenue earned from a business item minus its expenses. Third, technology evaluation represents the economic value of technology that can be generated through commercialization in terms of value, grade, or score (Park & Park, 2004; Sohn, Moon, & Kim, 2005). It is carried out to calculate the appropriate technology fee, review the feasibility of commercialization, and determine the investment share. This index is calculated by estimating the future cash flow generated by the technology, by comparing transaction cases of similar technologies, or by totaling up all costs invested in development.

Existing indices for enterprise evaluation were developed for specific purposes, so as to have the definite advantage of each. Credit rating is useful for determining the stability of enterprises' debts, and for this reason, it acts as a key factor in financing, enabling efficient information to be provided in the process of establishing credit transactions between enterprises and financial or investment institutions (Duffie & Singleton, 2003; Kronwald, 2009; Langohr & Langohr, 2010). Therefrom, it is easy to compare and analyze the performance of enterprises in relation to the business environment or market conditions, so that EVA acts as an important basis indicator for decision-making on investment and capital allocation (Arabsalehi & Mahmoodi, 2012; Chari, 2009). Technology evaluation can analyze the future growth potential of enterprises by considering those technology and innovation capabilities. This allows investors or financial institutions to predict the ability of enterprises to break new markets or lead an industry (Hall & Mairesse, 1995; Koller, Goedhart, & Wessels, 2010).

Although existing indices can evaluate enterprises from various perspectives, there are a couple of limitations. First, existing indices evaluate the enterprise in fragments. Each index selectively utilizes the information according to its own purpose. Credit ratings focus on the stability of fund recovery, and technology valuation is limited to information related to research and development (R&D). Second, the interpretability of evaluation result is insufficient. Results should be easily understandable what strengths good enterprises have or what weaknesses poor enterprises have. In addition, since enterprises of the same level have different characteristics, it is necessary to be able to identify differences through evaluation results. Last, existing indices are not completely objective in quantification. Although those are quantified evaluation, personal opinions or profit structures are also included. EVA reflects the opportunity cost of capital, which is not the actual cost, so the calculation result depends on the opinion of the evaluator. Credit rating reflects the profit structure of agencies, and include unofficial information gathered by analysts.

Based on these limitations of the existing indices, the characteristics that a new index should have for more practical and effective enterprise evaluation can be summarized as follows. *Diversified and objective evaluation*: rather than a fragmentary evaluation that selectively utilizes specific information, it should be possible to calculate not only the current situation of the company but also its potential value through a multifaceted evaluation that comprehensively reflects all information. In addition, objective indicators that do not include personal opinions or interests must be derived by using quantitative methods in the

Table 1
Comparison of properties of enterprise valuation methods.

Method	Data	Purpose	Algorithms	Scope
Zhang, Hu, & Zhang	Financial information	Evaluation of credit risk	SVM	Individual enterprise
Huang, Liu, & Ren	Financial information	Evaluation of credit risk	PNN	Individual enterprise
J. Chen, Liu, & Zhu	Financial information	Overall evaluation of risk and prospect	Clustering & LASSO	Individual enterprise
Proposed method	Financial information R&D information	Overall evaluation of risk and prospect	Clustering, PCA, & SSL	Multiple enterprises

evaluation process. *Interpretability of results*: by summarizing a lot of information to clearly understand the characteristics of the enterprise, it should be easy to interpret what characteristics the calculated evaluation results are attributed to.

In this study, we propose a machine learning-based enterprise evaluation method called *Enterprise Profiler*. As the name suggests, the proposed method comprehensively analyzes the characteristics of enterprise and evaluates not only the current status but also the potential prospect. Fig. 1 depicts the overview of the proposed method. Enterprise profiler includes two processes: *diversified quantification* and *semi-supervised evaluation*. At first, diversified quantification performs quantification that comprehensively reflects financial, employment, and R&D information. This process groups information that is similar to each other and extracts it into several remarkable features. Through diversified quantification, it is possible to clearly understand the features of enterprise. Next, semi-supervised evaluation uses enterprise features to perform evaluation and derives scores for each enterprise. The process selects several superior enterprises that have high ratings in all features and several inferior enterprises that vice versa, and compares the other enterprises against selected them. By constructing the enterprise network, the results are derived so that the evaluation scores of enterprises with similar features are also similar. Through this process, the objective evaluation can be performed without the intervention of personal opinions or profit structures. In summary, enterprise profiler analyzes financial, employment, and R&D information to understand enterprise features comprehensively and clearly through diversified quantification that extracts remarkable features, and based on this, performs objective evaluation by applying a network-based machine learning algorithm.

Our main contributions are summarized as follows. (a) We propose a machine learning-based enterprise evaluation method to identify not only the current status but also the potential prospect. (b) To perform diversified, interpretable, and objective evaluation, our method extracts remarkable features by quantifying various information and evaluates enterprises by comparing with the network via a graph-based semi-supervised learning. (c) We validate enterprise profiler and compare with an existing method, on which the proposed method has sufficient accuracy and includes the meaning of existing evaluation.

The remainder of the paper is organized as the follows. In Section 2, we introduce the previous studies on enterprise evaluation and describe the differentiation of the proposed method. In Section 3, the background and detailed description for the proposed method is presented with mathematical implementations. Section 4 shows the results for various experiments including the enrichment study. Section 5 and 6 concludes the paper with remarks on contributions and limitations of the proposed method.

2. Literature review

For a long time, there have been a lot of studies on how to quantitatively analyze and evaluate enterprises based on data. The financial indicators are used as the main data in most studies, and the analysis focuses on the identification of the solvency, profitability, operation, and development capacity of the enterprise (Chen, 2019), according to various contents in the financial statement, such as the balance sheet, income statement, and cash flow statement. The initial method of quantitative study on financial statements analyzed internal relations between main financial ratios and evaluated the financial status and economic benefits of enterprises (Scharkow, 2013). As the amount of information available has increased over time, methods for integrating various financial data have been developed, and studies have been conducted to understand the financial performance reflected behind the information (Lai & Chen, 2015).

With the development of the financial industry, credit rating came to be regarded as a major characteristic of enterprises, and the quantitative evaluation and analysis focused on finding out the financial risks (Gomoi, Pantea, & Cuc, 2021; Peng & Huang, 2020). In the analysis on financial risk, various methods applying machine learning algorithms have been developed for the purpose of more accurate evaluation. As representative studies, an index system for credit risk assessment was established by applying support vector machine (SVM) (Zhang, Hu, & Zhang, 2015), and the enterprise credit risk evaluation was performed based on probabilistic neural network (PNN) (Huang, Liu, & Ren, 2018). Although these studies evaluate enterprises, there is a limitation that other competencies are not considered as they focus on the capacity for debt repayment obligations.

The quantitative evaluation of enterprises has come to comprehensively consider not only the financial statements but also the potential capability of enterprises for future development. In recent years, an information integration approach combined with a traditional financial assessment of enterprises has been studied. This approach reflects the characteristics of enterprises from various aspects and evaluates not only the risk but also the prospect. For example, the Enterprise Capital Profit Model was proposed in (Chen, Liu, & Zhu, 2022), which the financial data is screened, analyzed, and diagnosed by the LASSO regression based on cluster analysis. Since the information integration approach evaluates both the development and risk of enterprises, the evaluation based on the relation between multiple enterprises is needed in consideration of the current state of the industry, rather than analyzing the individual strengths and weaknesses of an enterprise.

In this paper, we conduct evaluations using enterprise information in an integrated way. In addition, the proposed method derives comprehensive quantitative evaluation results for multiple enterprises by reflecting interactions between them in the same industry. The processes constituting the proposed method pursue high-accuracy performance based on machine learning algorithms. Table 1 compares the properties of the above-mentioned existing methods and the proposed method.

3. Proposed method

3.1. Background

At first, we briefly introduce three machine learning algorithms used in the proposed method: hierarchical clustering, principal component analysis, and graph-based semi-supervised learning.

Hierarchical clustering. As one type of cluster analysis, hierarchical clustering combines the most similar data point step-by-step with the entire data into one cluster (Jain & Dubes, 1988; Xu & Wunsch, 2005). As a result, this algorithm draws a dendrogram, which forms a hierarchical tree structure indicating the cluster formation in detail (Johnson, 1967). Hierarchical clustering is subdivided according to similarity measures and the linkage method (Ackermann, Blömer, & Sohler, 2010). To characterize similarity, measures include the correlation coefficient, cosine and Jaccard similarity, and the Euclidean, Manhattan, and Minkowski distances (Strehl, Ghosh, & Mooney, 2000). In this study, we calculate the correlation coefficient ρ as below:

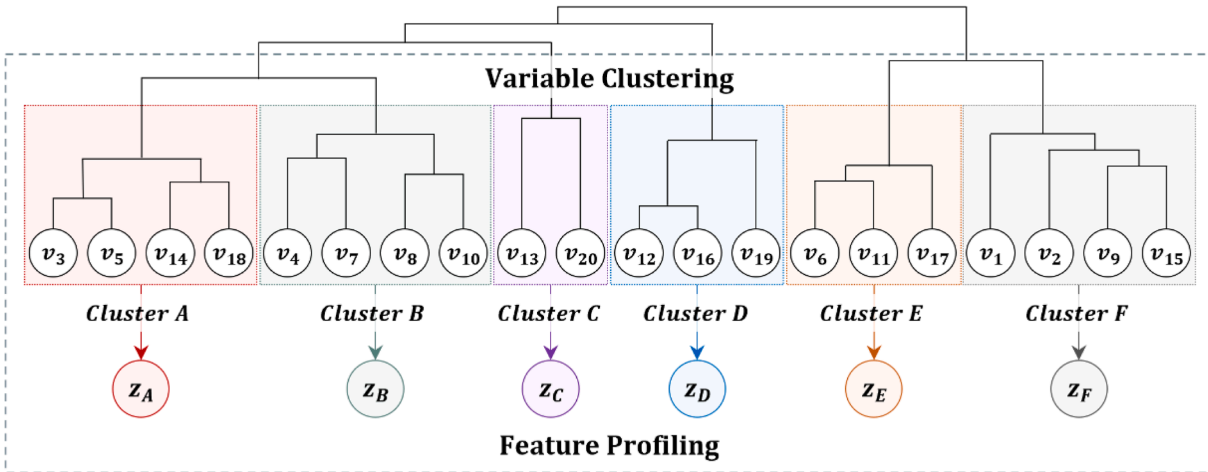


Fig. 2. Schematic description for diversified quantification. Diversified quantification firstly groups raw variables with high relevance into several clusters by hierarchical clustering, and then extracts each cluster as a single feature by principal component analysis.

$$\rho(x_i, x_j) = \frac{\sum_{k=1}^{p}(x_{ik} - \bar{x}_i)(x_{jk} - \bar{x}_j)}{\sqrt{\sum_{k=1}^{p}(x_{ik} - \bar{x}_i)^2}\sqrt{\sum_{k=1}^{p}(x_{jk} - \bar{x}_j)^2}} \tag{1}$$

where $\bar{x}_i$ indicates the average of x_i. Then, we cluster variables by the complete linkage between cluster U and V as follows:

$$d(U, V) = \max[d(x, y)|x \in U, y \in V] \tag{2}$$

Principal component analysis (PCA). The purpose of PCA is to reduce the dimensionality of the system (Schölkopf, Smola, & Müller, 1997; Van Der Maaten, Postma, & Van den Herik, 2009; Wold, Esbensen, & Geladi, 1987). Assuming there are n data points with p variables, and the raw data $\boldsymbol{X}$ has dimensions $n \times p$, projection matrix $\boldsymbol{W}$ consists of eigenvectors of $\boldsymbol{X}^{\mathrm{T}}\boldsymbol{X}$ as columns and dimensions $p \times p$. The feature space $\boldsymbol{Z}$ is defined as

$$\boldsymbol{Z} = \boldsymbol{X}\boldsymbol{W} \tag{3}$$

If $\boldsymbol{x}, \boldsymbol{w}, z$ indicates the row vector of $\boldsymbol{X}, \boldsymbol{W}, \boldsymbol{Z}$ respectively, the k^{th} principal components of $\boldsymbol{x}_{(i)}$ is defined as $z_{k(i)} = \boldsymbol{x}_{(i)} \bullet \boldsymbol{w}_{(k)}$ where $\boldsymbol{w}_{(k)} = (w_1, \cdots, w_p)_{(k)}$. Then, $\boldsymbol{w}_{(1)}$ is a transformation with the largest variance and is calculated as follows:

$$\boldsymbol{w}_{(1)} = \underset{\|\boldsymbol{w}\|=1}{\operatorname{argmax}}\left\{\|\boldsymbol{X}\boldsymbol{w}\|^2\right\} \tag{4}$$

Next, $\boldsymbol{w}_{(k)}$, when $k \geq 2$, is calculated as follows:

$$\boldsymbol{w}_{(k)} = \underset{\|\boldsymbol{w}\|=1}{\operatorname{argmax}}\left\{\|\widehat{\boldsymbol{X}}_k\boldsymbol{w}\|^2\right\}$$

where $\widehat{\boldsymbol{X}}_k$ indicates the data excluding up to the $(k-1)^{th}$ principal components from $\boldsymbol{X}$. Then, $\widehat{\boldsymbol{X}}_k$ is calculated as follows:

$$\widehat{\boldsymbol{X}}_k = \boldsymbol{X} - \sum_{i=1}^{k-1}\boldsymbol{X}\boldsymbol{w}_{(i)}\boldsymbol{w}_{(i)}^{\mathrm{T}}$$

Graph-based semi-supervised learning. Semi-supervised learning (SSL) performs well in the lack of label information by utilizing both labeled and unlabeled data (Bengio, Delalleau, & Le Roux, 2006; Chapelle, Scholkopf, & Zien, 2006; ZhuΓ & GhahramaniΓн, 2002). In graph-based SSL, data points and similarities between them are depicted as a graph (Kim, Lee, & Shin, 2019; Lee, Lee, Kim, & Shin, 2018). A connected graph $G = (V, W)$ is constructed where the nodes V represent the labeled and unlabeled data points, whereas the edges W reflect the similarity between the data points. The value of the similarity is represented by a matrix $W = \{w_{ij}\}$ where w_{ij} is the edge between nodes v_i and v_j. Then, w_{ij} is calculated by Gaussian function as below:

$$w_{ij} = \begin{cases} \exp\left(-\frac{\|v_i - v_j\|^2}{\sigma^2}\right)\text{if } i\ j\ (i\text{and } j \text{ are } k\text{-nearest neighbors}) \\ 0\text{otherwise} \end{cases} \tag{5}$$

If the numbers of total nodes, labeled nodes, and unlabeled nodes are n, l, and u, respectively, n would be the sum of l and u. Therefrom, we represent the label set as $\boldsymbol{y} = (y_1, \cdots, y_l, y_{l+1} = 0, \cdots, y_{n=l+u} = 0)^{\mathrm{T}}$ where $y_i \in \{-1, +1\}$ and $i = 1, \cdots, l$. The label information is propagated from labeled nodes to unlabeled nodes. The result of label propagation for $\boldsymbol{y}_i$ is defined as $\boldsymbol{f}_i = (f_{i_1}, f_{i_2}, \cdots, f_{i_l}, f_{i_{l+1}}, \cdots, f_{i_n})^T$ where $0 \leq f_{i_*} \leq 1$. Then, overall predicted value set is denoted as $\boldsymbol{f} = (\boldsymbol{f}_1, \boldsymbol{f}_2, \cdots, \boldsymbol{f}_k)$, which can be obtained by solving the quadratic objective function

$$\min_{f}(\boldsymbol{f} - \boldsymbol{y})^T(\boldsymbol{f} - \boldsymbol{y}) + \mu\boldsymbol{f}^T\boldsymbol{L}\boldsymbol{f} \tag{6}$$

where $\boldsymbol{L}$ is the graph Laplacian (Zhu, Ghahramani, & Lafferty, 2003), defined as $\boldsymbol{L} = \operatorname{diag}(\boldsymbol{W}) - \boldsymbol{W}$, and μ is a user-specified parameter which trades off the loss(the first term) and the smoothness(the second term). The solution is obtained as a closed form as below. The graph-based SSL has been well-established, and so further details can be found in (Chong, Ding, Yan, & Pan, 2020; Subramanya & Talukdar, 2014).

$$\boldsymbol{f} = (\boldsymbol{I} + \mu\boldsymbol{L})^{-1}\boldsymbol{y} \tag{7}$$

3.2. Diversified quantification

Diversified quantification summarizes raw data as a small number of features, thereby improving the interpretability of the enterprise evaluation. This process consists of two steps: *variable clustering* and *feature profiling*. The schematic description of this process is shown in Fig. 2.

Variable clustering. Raw variables with high relevance are grouped into a cluster by the hierarchical clustering algorithm. Assuming there is a dataset $\boldsymbol{X}$ that consists of m column vectors $\boldsymbol{v}_1, \cdots, \boldsymbol{v}_m$ with respect to each variable, then $\boldsymbol{X} = (\boldsymbol{v}_1, \boldsymbol{v}_2, \cdots, \boldsymbol{v}_m)$. The correlation coefficient $\rho(\boldsymbol{v}_i, \boldsymbol{v}_j)$ between $\boldsymbol{v}_i$ and $\boldsymbol{v}_j$ can be calculated by Eq. (1), and the variables are clustered by Eq. (2). As a result, all variables are clustered into k variable clusters by cutting off with a proper threshold.

Feature profiling. Each variable cluster is extracted into a single feature by applying PCA. We firstly construct subsets $\boldsymbol{X}_1, \cdots, \boldsymbol{X}_k$ by dividing raw data $\boldsymbol{X}$ into variables corresponding to each group. Then, the subsets of data for each variable group are derived into one profiling variable. The feature space for $\boldsymbol{X}_i$ is transformed into $\boldsymbol{X}_i\boldsymbol{P}_i$ by Eq. (3) where the projection matrix $\boldsymbol{P}_i$ is the eigenvector of $\boldsymbol{X}_i^{\mathrm{T}}\boldsymbol{X}_i$. The proposed

Table 2
Summary of the dataset by industry categories.

Category	# of enterprises	
Manufacturing	11,995	43.16 %
Real estate activities and renting and leasing	4,651	16.74 %
Wholesale and retail trade	3,410	12.27 %
Construction	1,857	6.68 %
Information and communications	1,119	4.03 %
Transportation	1,025	3.69 %
Professional, scientific, and technical activities	968	3.48 %
Others	2,765	9.95 %

method extracts the first principal component as the feature for each variable cluster by Eq. (4). As a result, by denoting z_i as the first principal component of X_iP_i, the overall feature set is denoted as $z = (z_1, z_2, \cdots, z_k)$.

3.3. Semi-supervised evaluation

The proposed method evaluates enterprises based on the profiled features. As shown in Fig. 1(b), this process starts with constructing the enterprise network. Enterprise Profiler seeks objective and quantitative evaluation by excluding the influence of personal opinions or profit structures. Therefore, with the network that is a useful method for representing relations, we evaluate enterprises by comparing only the features between enterprises. Enterprises are strongly connected when they have similar features and weakly connected in the opposite case. Therefrom, similar evaluation results can be drawn between strongly connected enterprises. Next, the superior and inferior enterprises are sorted, and by setting them as labels, the final evaluation is performed with the graph-based SSL. As a result, the more similar enterprises are to the superior, the better the evaluation, and vice versa.

Enterprise network. The network $G = (E, W)$ is constructed where the node set E represent the enterprises and the $W = \{w_{ij}\}$ represents a matrix of the similarity where w_{ij} is the weighted edge between nodes E_i and E_j. The Gaussian function in Eq. (5) is used to calculate the w_{ij}. For the label set, several superior and inferior enterprises are selected. We denote enterprises with the highest 1% value for each profiling feature as the superiors. To select the inferiors, we cite the criteria that the Bank of Korea selects the marginal enterprises (Kang, Kim, & Kim, 2020): (a) capital infiltration, (b) an interest compensation ratio of less than 100% over three years, and (c) operating cash flow minus over three years. In the label set $y_i \in \mathbb{R}^n$ for z_i, the superior enterprises are labeled as $+1$, the inferiors as -1, and others 0. The overall label set is denoted as $y = (y_1, y_2, \cdots, y_k)$.

Label propagation. The predicted value set f_i for y_i is derived by Eqs. (6) and (7). Finally, the total predicted value set $f = (f_1, f_2, \cdots, f_k)$ is averaged as follows to calculate the enterprise profiling score. The overall procedure for enterprise profiler is summarized in Algorithm 1.

$$EnterpriseProfilingScore = \frac{1}{k}\sum_{i=1}^{k} f_i$$

Algorithm 1. Enterprise profiler

Input: Dataset $\{X, y\}$
Output: Enterprise profiling score
(1) *Diversified quantification*
 (Variable clustering)
  Group raw variables into k clusters by (1) and (2)
 (Feature profiling)
  Extract each cluster as a feature by (3) and (4)
  Derive profiling feature set $z = (z_1, z_2, \cdots, z_k)$
(2) *Semi-supervised evaluation*
 (Enterprise network)
  Construct enterprise network $G = (E, W)$ by (5)
  Select label set $y = (y_1, y_2, \cdots, y_k)$
(*continued on next column*)

(*continued*)

Algorithm 1. Enterprise profiler

 (Label propagation)
  Predict labels $f = (I + \mu L)^{-1} y$ by (6) and (7)
  Calculate enterprise profiling score $\frac{1}{k}\sum_{i=1}^{k} f_i$
return Enterprise profiling score

4. Experimental results

4.1. Data description

The data used in this study was obtained from KISVALUE (https://www.kisvalue.com) which integrated information of enterprises, provided by Korea National Information & Credit Evaluation (NICE) credit rating. We collected data of 27,790 enterprises in 17 industries. Then, enterprises were divided into 8 categories according to the Korean Standard of Industry Classification (KSIC). The description for the collected data is shown in Table 2. The largest number of enterprises belonged to 'manufacturing' with 11,995 (43.16%), and the smallest category was 'professional, scientific, and technical activities' with 968 (3.48%). The dataset includes 113 variables of financial and R&D information. In detail, there are 108 variables of financial ratios and derived 5 variables from R&D cost: R&D cost/net sales, R&D cost/total current assets, R&D cost/capital stocks, R&D cost/personnel expenses, and R&D cost/total non-current assets. Table 3 shows all variables used in this study.

4.2. Results for diversified quantification

Diversified quantification was performed in the following order: variable clustering and feature profiling. First, we carried out hierarchical clustering on the dataset and cut-off clusters with a threshold that each cluster includes a bunch of variables with high correlations more than five. As a result of the variable clustering, 53 variables were grouped into seven clusters. Next, we extracted seven features from clusters by applying PCA. Then, we named each feature by considering the characteristics of variables; business profitability (BP), coverage elasticity (CE), financial soundness (FS), operation efficiency (OE), capital utility (CU), production efficiency (PE), and technology potentiality (TP). Results for variable clustering and descriptions of profiled features are shown in Table 4 and summarized in Table A of the Appendix.

In summary, first, by operating efficiency and business profitability, it is identified that how well the operating activity factor and profit rate indicator are used to generate sales revenue or cash. Second, by coverage elasticity and financial soundness, it is indicated that how much the debt can be repaid with revenue or equity. Third, capital utility and production efficiency denote how effectively capital was used and how efficiently enterprise resources were used. Last, technology potentiality represents how important the enterprise is to R&D and how much it conducts activities. As a result, the information of enterprises is diversified quantified by the proposed method.

4.3. Results for semi-supervised evaluation

Semi-supervised evaluation was performed in the following order: enterprise network construction and label propagation. First, the dataset was converted as 27,790 × 7 dimension with profiling features. The enterprise network was constructed by Eq. (5). For the superior enterprises, the highest 1% for each profiling feature, are selected with the label of $+1$. Then, through the criteria of the Bank of Korea, aforementioned in Section 2.2., the inferior enterprises are set with a label of -1. As a result, in the label set, the number of superior enterprises was 279 and the inferior enterprises was 550. Table 5 shows label information for category. In manufacturing, the superiors and the inferiors were

Table 3
Raw variables in the dataset.

Financial Information		
Growth ratio		
Total asset growth	Shareholder equity growth	Income before income tax expense growth
Tangible asset growth	Net sales growth	Net income growth
Current asset growth	Operating income growth	No. of employee growth
Inventory growth		
Profitability ratio		
Operating income to total assets	Operating income to net sales	Income before income tax expense to total assets
Net income to total assets	Total expenses to total revenue	Income before income tax expense to capital stock
Income before income tax expense	COGS to net sales	Income before income tax expense to equity
Operating income to operating capital	Depreciation ratio	Income before income tax expense to net sale
Net income to shareholder equity	Depreciation/total cost	Net income before financial expenses to avg. total assets
Net income to capital stock	Personnel expenses/ total cost	Times interest earned-operating act. basis
Net income to net sales	Taxes/Income before income taxes	Times interest earned-operating income basis
Gross profits to net sales	Taxes/total cost	Times interest earned-ordinary income basis
Dividend ratio	Financial expenses/total liabilities	Times interest earned - income before income taxes basis
Dividend to net income	Financial expenses/total borrowings	EBIT/net sales
Coverage ratio	Financial expenses/total expenses	EBITDA/net sales
Debt coverage ratio	Financial expenses/net sales	EBITDA/financial expenses
Loan efficiency ratio		
Leverage ratio		
Equity to total assets	Total borrowings to total assets	Total CF to total borrowings
Current ratio	Total borrowings to shareholder's equity	Total C/F to total assets
Quick ratio	Total borrowings/net sales	Total C/F to net sales
Cash ratio	Total liabilities to shareholder's equity	Inventories to NWC
A/R to trade account payable	Trade account payable to inventories	NWC to total assets
A/R to merchandise & finished goods	Total CF to total liabilities	Reserves ratio
Current liabilities to shareholder's equity	Net CF to total borrowings	Reserves to total disposal amount of R/E
R/E to total assets	Non-current assets ratio	Non-Current liabilities to NWC
R/E to paid-in capital	Non-current assets to equity & LT liabilities	Non-Current liabilities to shareholder's equity
Composition of value added		
Financial expenses to value added	Taxes & dues to value added	Income before income taxes to value added
Personnel expenses to value added	Rent to value added	Depreciation to value added
Activity ratio		
Total assets turnover	Non-Current assets turnover	WIP turnover
Equity turnover	Tangible assets turnover	A/R turnover
Paid-in capital turnover	Inventories turnover	Trade account payable turnover
NWC turnover	Merchandise & finished goods turnover	Inventories turnover 2
Operating capital turnover	Raw materials turnover	Net operating capital turnover

Table 3 (*continued*)

Financial Information		
Productivity ratio		
Value- added per employee	Machinery & equipment per employee	Labor cost to value added
Value added to net sales	Total assets per employee	Avg. tangible assets, net of CIP per employee
Net sales per employee	Efficiency of investment-avg. total assets	Income before income tax expense per employee
Net income per employee	Efficiency of investment-avg. machinery	Efficiency of investment-avg. tangible assets, net of CIP
Personnel expenses per employee		
R&D Information		
R&D cost/net sales	R&D cost/total current assets	R&D cost/capital stocks
R&D cost/personnel expenses	R&D cost/total non-current assets	

almost identical, whereas the inferiors were more than the superiors in other industries. Fig. 3 shows the network of representative superior enterprises in the manufacturing.

As a result of enterprise network, Fig. 3 depicts the toy network for superior enterprises in manufacturing. There are five representative items (electronics, automobile, medicine, chemicals, and metals) separated by different colors. For each item, the most superior enterprises are gathered in the highlighted area in the center of network.

Next, labels were propagated on the enterprise network, and Enterprise Profiler (EP) scores were derived. Following EP score, enterprises were classified into five EP grades as follows: EXC (excellent, top 15%), GOOD (15%–50%), TLR (tolerable, 50%–80%), POOR (80%–95%), and ISV (insolvent, 95%–100%). The EXC grade represents an extremely strong enterprise with outstanding competence in all aspects, and the GOOD grade demonstrates an extraordinarily strong enterprise that shows stable operation and growth, although the capability is slightly lower than that of the excellent grade. In the TLR grade, an enterprise is strong and generally stable, but has some unstable factors that may be affected by changes in the external environment, such as economic policies and market conditions. The POOR grade includes enterprises with adequate and unstable competence. They are capable of facing major future uncertainties, requiring overall improvement for stabilization. Finally, the ISV grade shows an enterprise that is highly vulnerable or is already in bankruptcy and default. This simplification improves the interpretability of enterprise evaluation by making the results more concise and intuitive to understand. Definition of each grade is provided in Table B of the Appendix.

Fig. 4 depicts the results for semi-supervised evaluation in manufacturing. At first, Fig. 4(a) represents the distribution of EP score. Most enterprises in EXC shows EP score close to 100, whereas ISVs are almost 0. It indicates that EXC enterprises are extremely strong in all aspects, and ISV enterprises are almost in default in that they are highly vulnerable in general. In the case of the GOOD grade, which accounts for the largest proportion, it shows a score range between about 60 and 90, indicating stable operation and growth. Meanwhile, a noticeable score change is shown in the TLR grade. TLR enterprises score below 60 at EP score. The difference between the highest and lowest score was about 50. It can be seen that the instability of enterprise is sensed in the TLR grade. Also, POOR enterprises have very low scores and show a high level of risk, which means they are on the verge of bankruptcy.

Fig. 4(b) shows the case examples for the proposed method. One enterprise was selected for each EP grade, and their profiled features were shown in cases A to E by diversified quantification. The dotted lines denote the average value of enterprises in manufacturing. In the case of

Table 4
Results for diversified quantification.

(a) Operating Efficiency: an index to determine how efficiently sales activity (cost) factors are used to achieve sales goals.	
COGS to net sales	Financial expenses/net sales
Total borrowings/net sales	Total expenses to total revenue
	Value added to net sales
(b) Coverage Elasticity: an indicator to check how stable the business is by determining how much it is capable of repaying short-term debts with the profits earned through business activities for a certain period (fiscal year).	
Debt coverage ratio	Times interest earned-ordinary income basis
EBITDA/financial expenses	Times interest earned-operating income basis
Coverage ratio	Times interest earned-income before income taxes basis
	Times interest earned-operating act. basis
(c) Financial Soundness: an indicator of the soundness of debt management that evaluates the ability to repay debt to total capital (or equity capital).	
Non-current assets ratio	Non-current liabilities to shareholder's equity
Total borrowings to total assets	Total borrowings to shareholder's equity
Current liabilities to shareholder's equity	Total liabilities to shareholder's equity
(d) Business Profitability: an indicator to identify the degree of creation of book and actual cash flows by classifying various enterprise profit margin indicators into realization and cash basis.	
Total C/F to net sales	Net income to net sales
EBIT/net sales	Operating income to net sales
EBITDA/net sales	Operating income to operating capital
	Income before income tax expense to net sale
(e) Capital Utility: an indicator of whether capital is being used efficiently by measuring how much total capital (or equity capital) has influenced profit-generating activities and the importance of the role as capital itself.	
Equity to total assets	Operating income to total assets
NWC to total assets	Income before income tax expense to total assets
R/E to total assets	Income before income tax expense
Net income to total assets	Income before income tax expense to equity
Net income to shareholder's equity	Net income before financial expenses to avg. total assets
(f) Production Efficiency: an index that determines how efficiently resources are used to generate profits (or profits) of a company.	
Dividend ratio	Operating capital turnover
Paid-in capital turnover	Value-added per employee
Net income to capital stock	Personnel expenses per employee
Net income per employee	Income before income tax expense to capital stock
Total assets turnover	Income before income tax expense per employee
R/E to paid-in capital	Efficiency of investment-avg. total assets
	Efficiency of investment-avg. machinery
(g) Technology Potentiality: an index to determine how important R&D is and how much a company engages in R&D activities by identifying the proportion of R&D expenses in sales, profits, and assets.	
R&D cost/net sales	R&D cost/personnel expenses
R&D cost/capital stocks	R&D cost/total current assets
	R&D cost/total non-current assets

A and B belonging to the upper grade, the profiling features are generally higher than the average. In particular, CU is high compared to other enterprises in that those enterprises efficiently use their capital to generate profit from business activities. Also, TP is also remarkable. TP of enterprises belonging to the upper grade is significantly higher than that of the lower grade enterprises. It indicates that the upper grade enterprises value R&D and invest a lot of resources. Therefrom, it can be seen that enterprises that received high evaluation in the proposed method are performing stable operation and business activities by generating profits through efficient capital utilization. It was also found that they regard R&D important so that they prepare for the future and increasing growth potential by improving its technology through a lot of investment.

Table 5
Label information by industry categories.

Category	Superior	Inferior
Total	**279**	**550**
Manufacturing	120	121
Real estate	47	175
Wholesale and retail trade	34	45
Construction	19	40
Publishing, broadcasting, and information	11	16
Transportation	10	21
Professional, scientific, and technical activities	10	21
Others	28	111

4.4. Results on validity of enterprise profiler

In this subsection, we describe experimental results on validity of the proposed method. To validate enterprise profiler, we derived the accuracy of the label propagation results performed in semi-supervised evaluation. The performance was measured by the area under receiving operating characteristic curve (AUC), and the entire experiment was repeated 100 times with five-fold cross validation. Fig. 5(a) shows the AUC results for enterprises in manufacturing. The average AUC for the proposed method was 0.823, the highest AUC among repetitions was 0.847 and the lowest AUC was 0.802. Enterprise profiler showed more than 80% accuracy with AUC performance.

Additionally, we compared the proposed method with EVA. We calculated EVA ratio which is divided into EVA^+ and EVA^-. The EVA^+ indicates that the enterprise creates profits and value, whereas EVA^- indicates the opposite. Therefore, by comparing the ratio, we can simply determine the degree of value creation. Fig. 5(b) depicts the comparison results. The results shows that the higher EP grade, the higher the EVA^+, and the lower of EP grade, the higher EVA^-. From the comparison result, enter profiler well reflects the value creation of enterprises. This can be seen as including the meaning and purpose of EVA. Therefore, the proposed method includes the purpose of the existing method in performing enterprise evaluation reflecting comprehensive information, and that the result is also accurately derived.

4.5. Results for comparison experiments

We further conducted experiments to compare the proposed method with the existing methods developed for enterprise evaluation. The comparison experiment consists of three parts. First, we compare the distributions of the two sets of variables profiled by the proposed method and the existing method (J. Chen et al., 2022), using t-SNE visualization (Van Der Maaten, 2014; Van der Maaten & Hinton, 2008). Next, we construct enterprise networks from each of the two variable sets and compare the similarity between the labeled data, using various metrics for network linkage analysis (Abbas et al., 2021): common neighbors (CN) (Newman, 2001), Salton index, (Chowdhury, 2010), Sorensen index (Sorensen, 1948), Hub Promoted Index (HPI) (Ravasz, Somera, Mongru, Oltvai, & Barabási, 2002), Hub Depressed Index (HDI) (Lü & Zhou, 2011), and Leicht–Holme–Newman Index (LHN-I) (Leicht, Holme, & Newman, 2006). Finally, we compare the classification performance of applying various machine learning algorithms including SVM, PNN, and LASSO used in previous studies described in Section 2 as well as Naïve Bayes (NB), k-Nearest Neighbors (kNN), Linear Discriminant Analysis (LDA), Decision Tree (DT), Random Forest (RF), and Deep Neural Networks (DNN) (Dong, Xia, & Peng, 2021). The experimental

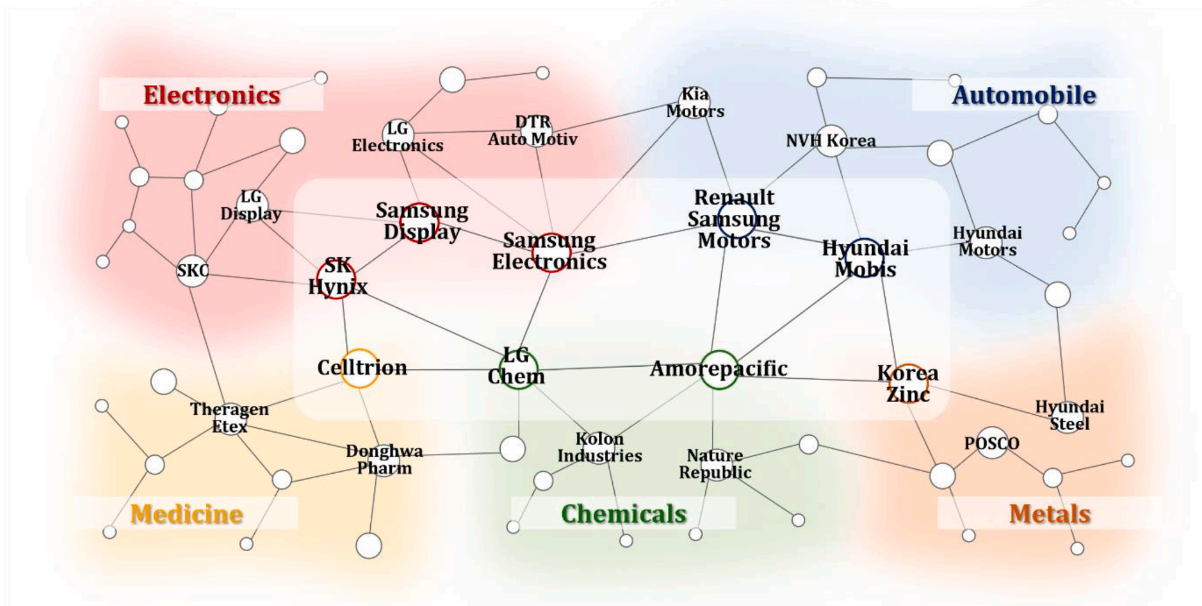


Fig. 3. Network for superior enterprises in manufacturing.

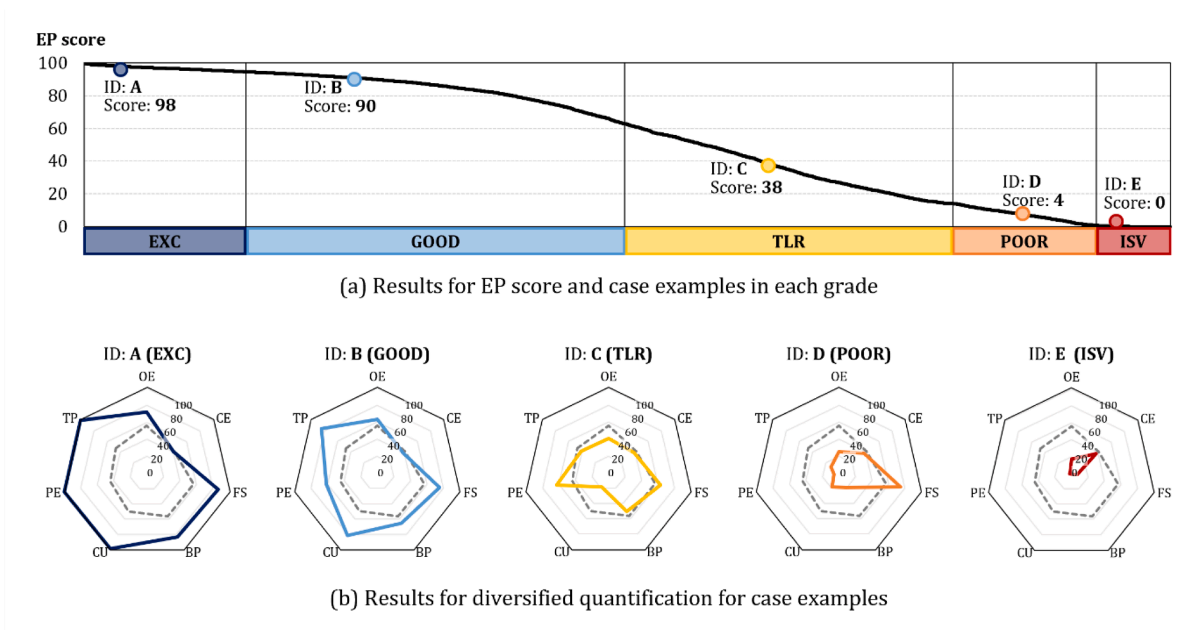
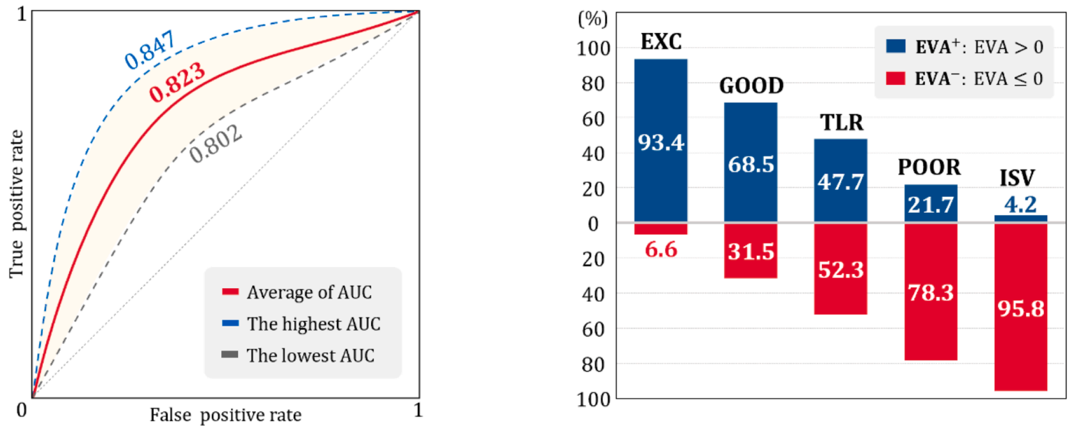


Fig. 4. Results for semi-supervised evaluation in manufacturing.

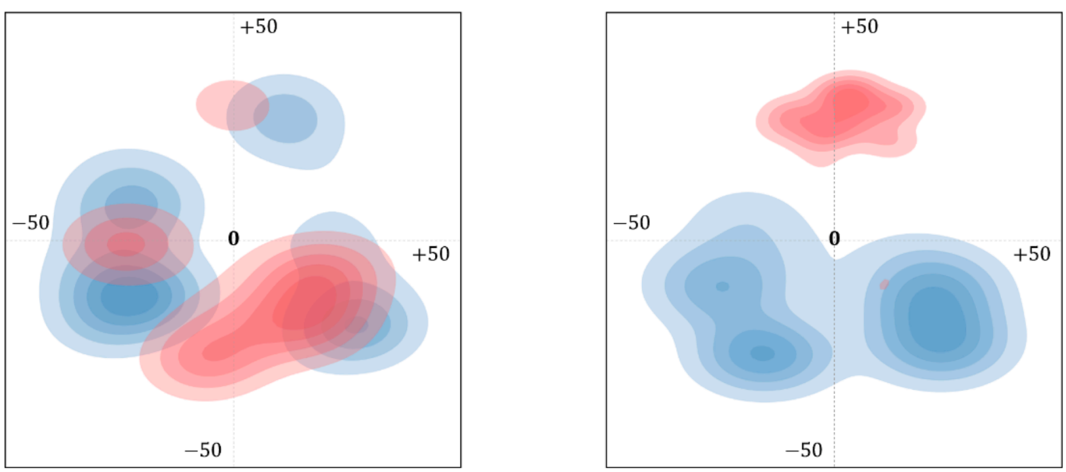
settings were the same as the experiments for the proposed method, and the performance was measured by AUC for 100 repetitions with five-fold cross validation.

Results for the three comparison experiments are presented in Fig. 6, Table 6, and Fig. 7 in turn. First, comparison results for the visualized distributions of profiled variable sets are shown in Fig. 6. The red and blue areas show the distribution of inferior and superior enterprises, respectively. As a result of variable profiling by the comparison method, the distributions between inferior and superior enterprises are mixed, and the difference of distributions is not clear. On the other hand, the results by the proposed method show clearly differentiated distributions for the two groups of enterprises. Second, Table 6 represents the comparison of metrics for network linkage analysis, indicating the average of identically labeled enterprises. The results of Table 6 show that the proposed method outperforms the comparison method in all metrics. Therefrom, it can be seen that the similarity of intra-class is further improved when profiling variables using the proposed method rather than the comparison method. Third, Fig. 7 depicts the AUC comparison results. Lightly colored bars and dark colored bars represent the results of applying three algorithms to the profiled variables derived by the comparison method and the proposed method, respectively. As a result, the enterprise evaluation results for the comparison method and the proposed method respectively showed AUC performance of 0.704 and 0.757 on average. This indicates that utilizing the profiled variables by the proposed method leads to 7.5% better enterprise evaluation results on average. In addition, all algorithms did not reach the AUC



(a) AUC results for enterprise profiler (b) Comparison results with EVA

Fig. 5. Results on validity of enterprise profiler.



(a) Comparison method (b) Proposed method

Fig. 6. Comparison for visualized distributions of profiled variable sets. (a) and (b) depict t-SNE visualization results for variable profiling by the comparison method and the proposed method, respectively. Red and blue shows the distribution of profiled variables for inferior and superior enterprises, respectively.

Table 6
Comparison for linkage analysis on enterprise networks.

Category	Metrics for network linkage analysis					
	CN	Salton	Sorenson	HPI	HDI	LHN-I
Comparison method	0.087	0.062	0.006	0.008	0.005	0.071
Proposed method	0.354	0.134	0.035	0.040	0.031	0.095

performance of 0.823 of SSL applied in this study. Consequently, the proposed method enables more accurate enterprise evaluation by performing variable profiling that better differentiate the enterprise's capabilities, and SSL on the enterprise network yields the best performance.

4.6. Enrichment study

In this subsection, we describe results for enrichment study representing the usability of enterprise profiler. For this study, we performed the proposed method on enterprises in manufacturing. Then, we selected enterprises related to the automobile and semiconductor which are both major items of manufacturing in Korea. Fig. 8 show results for comparison between two items. At first, Fig. 8(a) indicates that the number of semiconductor enterprises is smaller than that of automobile enterprises, but the EP score is higher. Next, Fig. 8(b) represents the difference between the two categories of enterprises by grade. The ratio of semiconductor enterprises decreased significantly as EP grade got lower, but the ratio of automobile enterprises increased and exceeded the average. EXC grade is remarkable in that the semiconductor enterprises were at 29% which is twice as the average, whereas the automobile enterprises were at 9% which is a half of the average.

Through Fig. 8(c), it is shown why semiconductor and automobile enterprises showed differences in EP score and grade. Overall, semiconductor enterprises outperformed the manufacturing average, while automobile enterprises did the opposite. CU showed the biggest difference, and this result indicates that total capital of semiconductor enterprises was effectively and efficiently used to generate those profit. OE, FS, and BP also made noticeable differences. Through those difference of profiled features, it can be seen that it is important how well the operating activity generates sales revenue or cash for manufacturing companies and how efficiently the debt is used for business activities.

Additionally, Fig. 8(d)-(g) represent case examples of semiconductor and automobile enterprises in EXC. Each case is an enterprise rated close to the top 10% of the EP score. The figures show that the characteristics of each enterprises indicate a variety of patterns, even though they received similar ratings. Comparing the two enterprises belonging to

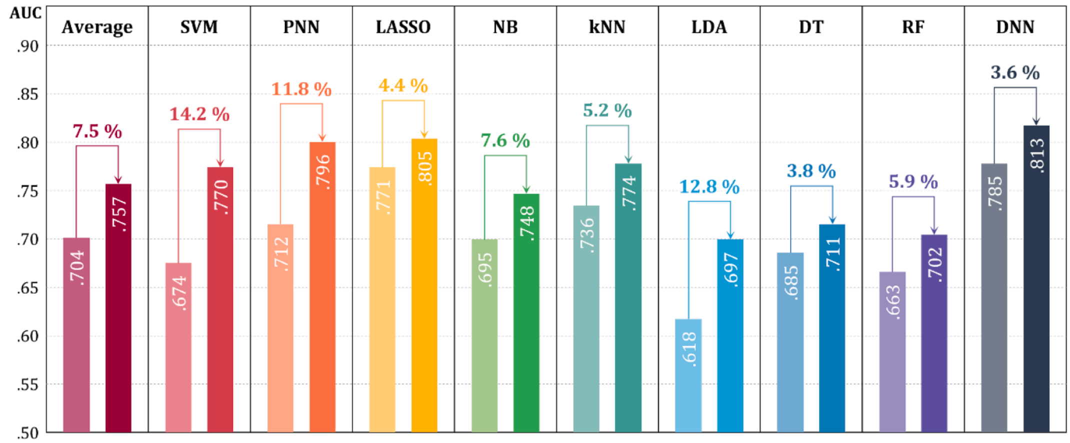
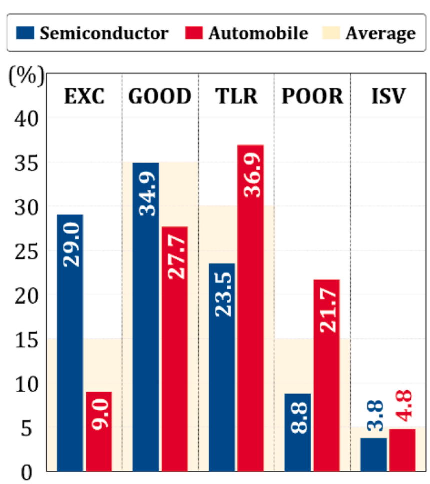


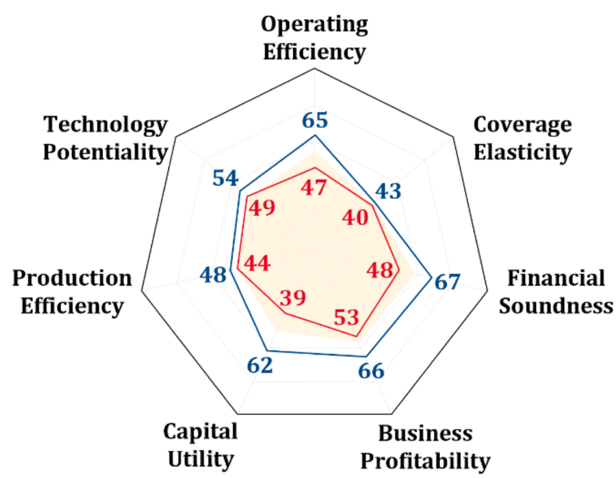
Fig. 7. Comparison for classification performance. Lightly colored bars and dark colored bars represent the results for enterprise evaluation with the profiled variables by the comparison method and the proposed method, respectively.

Item	# of enterprise	avg. of EP score	avg. of EP grade
Semiconductor	582	65	GOOD (top 39%)
Automobile	1,763	43	TLP (top 58%)

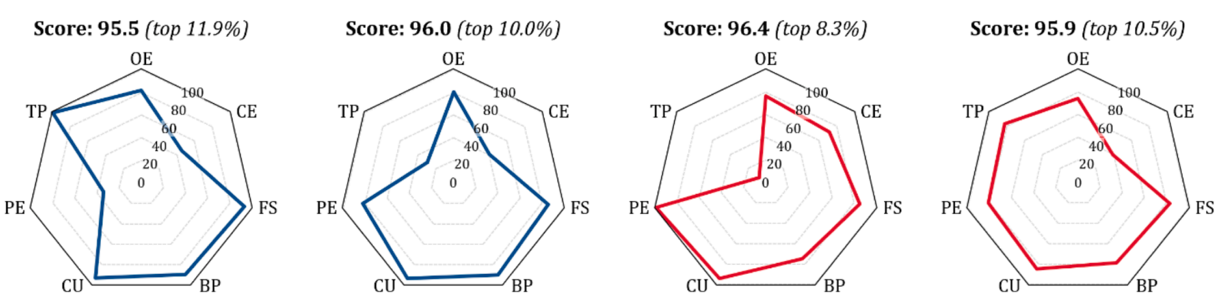
(a) Comparison results between semiconductor and automobile



(b) Distributions of EP score



(c) Results for feature profiling



(d) Semiconductor A (e) Semiconductor B (f) Automobile C (g) Automobile D

Fig. 8. Results for enrichment study.

Table A
Definitions for profiling variables derived by diversified quantification.

Abbreviation	Variable	Definition
OE	Operating Efficiency	OE determines how efficiently sales activity (cost) factors are used to achieve sales goals.
CE	Coverage Elasticity	CE checks how stable the business is by determining how much it is capable of repaying short-term debts with the profits earned through business activities for a certain period (fiscal year).
FS	Financial Soundness	FS indicates the soundness of debt management that evaluates the ability to repay debt to total capital (or equity capital).
BP	Business Profitability	BP identifies the degree of creation of book and actual cash flows by classifying various enterprise profit margin indicators into realization and cash basis.
CU	Capital Utility	CU indicates how efficiently capital is being used by measuring how much total capital (or equity capital) has influenced profit-generating activities and the importance of the role as capital itself.
PE	Production Efficiency	PE determines how efficiently resources are used to generate profits (or profits) of a company.
TP	Technology Potentiality	TP determines how important R&D is and how much a company engages in R&D activities by identifying the proportion of R&D expenses in sales, profits, and assets.

Table B
Definitions for enterprise grades derived by semi-supervised evaluation.

Abbreviation	Grade	Rank	Definition
EXC	Excellent	Top 15%	Extremely strong enterprise with outstanding competence in all aspects
GOOD	Good	15%–50%	Extraordinarily strong enterprise that shows stable operation and growth, although the capability is slightly lower than that of the excellent grade
TLR	Tolerable	50%–80%	Strong and generally stable enterprise, but including some unstable factors that may be affected by changes in the external environment, such as economic policies and market conditions
POOR	Poor	80%–95%	Enterprise with adequate and unstable competence, which is capable of facing major future uncertainties, requiring overall improvement for stabilization
ISV	Insolvent	95%–100%	Enterprise that is highly vulnerable or is already in bankruptcy and default

semiconductor, it appears that A places importance on technology and B focuses on productivity. For automobiles, C and D are all good features except for TP and CE, respectively. Considering that C has a very high PE, it can be seen that it generates profits by focusing on production and sales rather than development. For D, CE is low, but TP is high. Although a lot of investment is being made in R&D, it has not yet led to profits. However, since the rest of features are good, it is understandable that the enterprise is currently stable and has high growth potential based on R&D.

5. Discussion

This study purposes to develop a framework for enterprise evaluation. We considered the objectivity and generality of this framework to be key properties. For objective enterprise evaluation, it was intended to present both risks and prospects of enterprises by comprehensively reflecting as much information as possible without being biased toward a part of information. In addition, in order to be regarded as a general-purpose method that can be used in various datasets, well-established machine learning algorithms that have been verified through many data and existing studies was applied. Based on these purposes, we proposed a machine learning-based enterprise evaluation method called *Enterprise Profiler*. Our method aims to comprehensively analyze the characteristics of enterprise and evaluate not only the current status but also the potential prospect.

To implement our goal of this study, the proposed method consists of two processes: *diversified quantification* and *semi-supervised evaluation*. First, diversified quantification performs variable profiling that comprehensively reflects financial, employment, and R&D information. This process clusters information and extracts several features. Through diversified quantification, it is possible to clearly understand the features of enterprise. We extracted seven features: business profitability, coverage elasticity, financial soundness, operation efficiency, capital utility, production efficiency, and technology potentiality. In comparison results with the existing method (Chen et al., 2022), the profiled variables by the proposed method better differentiated between inferior and superior enterprises. Second, semi-supervised evaluation uses profiled variables to perform evaluation and derives scores. This process selects several enterprises as labels, which have high ratings in all features and vice versa. The other enterprises are compared against labels on the enterprise network. By applying graph-based SSL, labels are propagated on the network, and scores are derived so that enterprises with similar features are also similar in evaluation results. We validated enterprise profiler and compared with an existing method. The experimental results indicate that the proposed method has sufficient accuracy and includes evaluation by the existing method. Also, the comparison results with other algorithms in existing methods showed that the proposed method was the most accurate.

It is considered that the main reason why the proposed method showed better results than the existing method was the comprehensive use of information, based on the results for further analysis that were able to identify the characteristics of enterprises in detail for each business item within the same industry. In terms of methodology, it seems that the fact that the profiled variables were formed into a network and the similarity between enterprises was used led to accurate classification results. When there are few labels that the algorithm can learn, it is considered that the use of not only the labels but also the relationship formed between the data, such as manifold, was effective in deriving high accuracy.

6. Conclusion

In this study, we propose a machine learning-based enterprise evaluation method, namely *Enterprise Profiler*, consisting of diversified quantification and semi-supervised evaluation. The most pronouncing feature of the proposed method is to evaluate enterprises on the enterprise network constructed by the profiled variables from comprehensive information. This approach evaluates multiple enterprises at once by comparing the characteristics of enterprises, and the results reflect both the risks and prospects of them. We validated the proposed method on the dataset of 27,790 enterprises with 113 variables about financial and R&D information. Experimental results indicate that the proposed method extracts variables, distinguishing the characteristics of enterprises more clearly, and therefrom, the results are more accurate than the comparison methods. We also showed that the results of enterprise evaluation by the proposed method reflect the industrial situation, demonstrating practical utility. Consequently, the proposed method can be used as an objective and general framework for enterprise evaluation.

On the other hand, the advantages of this study also suggest issues that need to be supplemented in the future. In real-world, far more than audited enterprises exist but are outside the scope of this study. Especially, for research institutes or start-up in small scale that recently increases, the amount of data for is not enough to evaluate. Considering this issue, the proposed method will be improved for the evaluation to enterprises with insufficient data. Additionally, in order for the proposed method to be more practical, it needs to include not only the evaluation but also the prediction. As a future, we are preparing a study to derive the trend of future enterprise evaluation through time series prediction by setting the score of the proposed method as a target variable.

CRediT authorship contribution statement

Sunghong Park: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft, Visualization. **Kanghee Park:** Conceptualization, Methodology, Formal analysis, Validation, Writing – review & editing, Funding acquisition. **Hyunjung Shin:** Conceptualization, Methodology, Investigation, Funding acquisition, Supervision, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Appendix

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