# Turnover Prediction In Human Resource Management Via Deep Variational Information Bottleneck

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Turnover prediction of employees has become a key focus for human resource specialists, as it is broadly viewed as a vital measure of an organization's competitive edge. To this end, a new deep variational information bottleneck network based turnover prediction method is proposed for human resource management (TP-VIB). Specifically, The information bottleneck is utilized to model the turnover prediction task, and then variational inference method is used to obtain lower bound of the IB for optimizing representation learning and pattern mining networks within the deep framework. Furthermore, a entropy regularization term is designed to balance positive and negative class imbalances in employee turnover datasets. Finally, the experiment results demonstrate that TP-VIB sets a new baseline method for employee turnover prediction tasks.

**Keywords:** Turnover prediction; information bottleneck; deep framework

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Human resource management is at the core of company operations [1]. Effective HR management involves handling the division of labor and collaboration among employees, enabling each individual to maximize their potential and enhance operational efficiency. It helps companies generate more productivity, improve production efficiency, and create economic value. Data mining methods find numerous applications in the field of human resources, including recruitment, performance evaluation, job fit analysis, and salary adjustments [2–5]. These methods aim to identify issues in human resource allocation by analyzing employee data, providing guidance for management. Traditional HR management relies on the individual capabilities of HR personnel, managing employees based on human perception, which may overlook many important issues. In contrast, data mining methods focus on the data itself, uncovering patterns through algorithms to reveal features that may go unnoticed by humans. Providing these features to frontline HR workers can offer more targeted guidance, significantly enhancing efficiency. Turnover prediction algorithms can promptly identify employees with intentions to leave, prompting managers to communicate with them in a timely manner and mitigate unnecessary losses.

Turnover prediction algorithms can assist companies in correcting management issues. Often, due to managerial shortcomings such as unreasonable incentive schemes or mismatched job assignments, employee satisfaction tends to be low, leading to high turnover rates. For managers within the company, these managerial shortcomings are often difficult to detect. However, through technological means, analyzing the reasons behind high turnover rates can enable companies to address these issues at their core, thereby reducing turnover rates. Among numerous studies, data-driven employee turnover prediction methods have garnered significant attention, typically branching into two categories: machine learning-based turnover prediction often involves training algorithms on large datasets to identify and predict the likelihood of employee turnover [6–8]. Survival analysis-based turnover prediction methods focus on analyzing the risk of employees leaving within specific timeframes and the various factors influencing this risk [9–11].

However, Current turnover prediction methods encounter two primary challenges. First, machine learning-based approaches construct and train complex algorithmic models using historical data to predict employee turnover likelihood. These methods employ various techniques, including decision trees, random forests, support vector machines, and neural networks, to identify turnover-related factors through feature engineering and pattern recognition. Despite achieving reasonable prediction accuracy, these models often lack interpretability, hindering business managers' understanding of the decision-making process and model logic. Second, survival analysis-based methods focus on analyzing the risk of employee turnover within specific timeframes, considering the impact of time on turnover risk. While useful for estimating turnover timing and identifying key retention factors, survival analysis may not capture all complex turnover factors, especially in multidimensional organizational environments with individual employee differences. In summary, while machine learning-based methods offer predictive accuracy, they lack interpretability, while survival analysis-based methods provide timing insights but may overlook complex turnover factors. These challenges highlight the need for future research to develop interpretable models that effectively capture the multidimensional nature of turnover dynamics.

TP-VIB integrates the nonlinear modeling capabilities of deep learning with the guiding principles of information bottleneck theory. It aims to reduce model complexity and overfitting risks while retaining valuable information for predicting employee turnover. The core idea of TP-VIB is to strike a balance between preserving the predictiveness of data representations and reducing unnecessary information redundancy. By introducing the constraint of the information bottleneck, TP-VIB encourages the model to learn compact and meaningful data representations, thereby enhancing its generalization ability and prediction accuracy on unseen data. One key advantage of TP-VIB is its enhanced interpretability. It emphasizes the correlation between data representation and the target task, allowing business managers to gain insights into the factors influencing employee turnover more clearly. This improved interpretability helps managers understand the underlying reasons for turnover and formulate more effective talent retention strategies. In summary, TP-VIB offers a novel approach to employee turnover prediction by leveraging the strengths of deep learning and information bottleneck theory. It aims to address the shortcomings of traditional methods in terms of interpretability and generalization ability, ultimately assisting businesses in managing talent turnover more effectively.

TP-VIB makes three notable contributions, including:

- A new deep variational information bottleneck within the deep framework is designed for turnover prediction in human resource management, which effectively mines patterns of employee turnovers. Furthermore, the variational inference method is used to obtain lower bound of the information bottleneck for model optimizing.
- A entropy regularization term is introduced to balance positive and negative class imbalances in employee turnover datasets, which helps improve the robustness and generalization capability of the turnover prediction model.
- Extensive results on the real-world employee dataset showcase that TP-VIB sets a new benchmark in the turnover prediction in human resource management, highlighting the effectiveness of TP-VIB in pushing the boundaries of performance on challenging human resource management tasks.

The subsequent segments of TP-VIB are organized: Section II presents a comprehensive analysis of modern methodologies in employee turnover prediction of human resource management. Section III delineates fundamental components and methodology of TP-VIB. Section IV elaborates on the experimental results and analysis. Ultimately, Section V provides the final thoughts.

## 1. Related works

This section delves an extensive data-driven frameworks for turnover prediction within human resource management [3, 7]. For example, Kim et al. utilized the random forest to define an employee turnover prediction model, capturing key information by analyzing the dependencies of turnover decision variables, thereby enhancing the performance of employee turnover prediction [6]. By embedding GBDTs into the CRAT model, Kang and colleagues' research not only enhanced the model's predictive accuracy for employee turnover intentions but also strengthened the model's capability to explain the causal relationships behind employee turnover behavior[12]. Nagadevara and Srinivasan utilized logistic regression to model the correlation between demographic attributes and employee absenteeism with employee turnover, achieving a prediction accuracy of 79.58% [13]. Nesreen et al. adopted a more advanced machine learning technique, utilizing the XGBoost algorithm to model the relationships between variables from online-collected resume data to predict employee turnover [14]. XGBoost is an efficient gradient boosting decision tree algorithm that excels in handling large-scale datasets and complex models, offering higher predictive accuracy than traditional methods. Alsubaie et. al took an integrated approach, combining multiple machine learning paradigms to jointly analyze the key variables that influence employee turnover, achieving pattern mining for turnover prediction [15]. This multi-model fusion method can fully leverage the advantages of different algorithms, enhancing the model's generalization capability and predictive performance. By considering a variety of factors, this method helps to reveal the complex patterns of employee turnover and provides organizations with more comprehensive and in-depth insights. Cai et al. construct dynamic graph relationships between employees and companies to fit the correlations within the data, incorporating temporal information to enhance employee turnover prediction [16]. Park et al. generate new sample points through interpolation between different categories of employee turnover, increasing the quantity of samples in the minority class, thereby balancing the class distribution to enable better recognition of the minority class [17]. Liu et al. propose a comprehensive multisource learning framework that is capable of adapting to the continuous changes in social network data. By updating and re-evaluating the model in real-time, it ensures that the predictive accuracy of the model is maintained [18]. Jin et al. couple survival analysis with machine learning into a unified framework, deeply mining the historical behavior and information of departing employees to enhance the performance of employee turnover prediction [10]. Guerranti and Dimitri first conducted key feature selection in the data based on the Pearson correlation coefficient, and then implemented a predictive model for employee turnover using an ensemble paradigm of base classifiers such as decision trees [19].

In the current landscape of employee turnover prediction research, the predominant reliance on traditional machine learning and survival analysis techniques poses several notable issues and limitations. (1) traditional machine learning models often necessitate manual feature engineering, a process that can be time-consuming and prone to overlooking significant data features. Conversely, deep learning models possess the capability to automatically extract complex features from large datasets with minimal human intervention. This capacity potentially enables the discovery of underlying causes of employee turnover more effectively. (2) machine learning and survival analysis models may lack the flexibility of deep learning models in

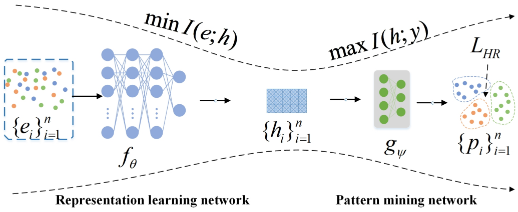


**Fig. 1.** The illustration of TP-VIB. Specifically, given a data set of $n$ employees $E = \{e_i, y_i\}_{i=1}^n$, TP-VIB minimizes mutual information between data $e$ and representation $h$, i.e., $I(e;h)$ to eliminate label independent information from data in the representation learning network $f_\theta$ and maximizes mutual information between representation $h$ and label $y$, i.e., $I(h;y)$ to predict labels as much as possible in the pattern mining network $g_\psi$. Furthermore, an entropy regularization term $L_{HR}$ is used to balance positive and negative class imbalances in the employee turnover prediction.

handling non-linear relationships and interaction effects. Given that the reasons for employee turnover often stem from multifaceted factors encompassing social, economic, and psychological aspects, deep learning models, particularly complex network structures like Convolutional Neural Networks and Recurrent Neural Networks, are better equipped to manage such nonlinearity and dynamic data changes. (3) deep learning models exhibit advantages in managing large-scale datasets. With the continuous growth in corporate data volume, traditional machine learning models may encounter performance bottlenecks. In contrast, owing to their high parallel processing capabilities and scalability, deep learning models can effectively address these challenges associated with big data, thereby enhancing the accuracy and scalability of turnover prediction models.

## 2. Turnover prediction in human resource management via deep variational information bottleneck

Consider a data set of $n$ employees $E = \{e_i, y_i\}_{i=1}^n$ in the human resource management, where $e_i \in R^d$ denotes the data of the $i$-th employee and $d$ is data dimension. $y_i \in R^K$ denotes the label of the $i$-th employee and $K$ is label number. A new deep variational information bottleneck network is proposed for predicting employee turnover in human resource management (TP-VIB), as shown in Fig. 1. Specifically, TP-VIB utilizes a deep feature extractor to map samples from the data space into the feature space, learning intrinsic low-dimensional representations. Then, TP-VIB conducts a classification network to identify and capture

**Table 1.** Frequently used notations.

| Notations | Description |
|---|---|
| $n$ | The number of employees. |
| $e_i$ | The data of the $i$-th employee. |
| $p_i$ | The corresponding turnover prediction of $e_i$. |
| $d$ | The data dimension. |
| $y_i$ | The label of the $i$-th employee. |
| $f_\theta$ | The feature extractor. |
| $g_\varphi$ | The classifier network. |
| $I(;)$ | The mutual information function. |
| $exp(\cdot)$ | The exponential function. |

employee turnover patterns from representations. Finally, TP-VIB uses the information bottleneck with a regularization term in the deep framework to balance information compression and pattern mining, achieving the robust turnover prediction for human resource management. The mathematical notations defined in TP-VIB are presented in Table 1.

Next, TP-VIB is introduced in detail from two aspects: the network architecture and the loss function.

### 2.1. The network architecture

In this section, TP-VIB conducts the representation learning network and the pattern mining network based on deep frameworks to obtain turnover prediction for the human resource management.

Specifically, given the data $e_i$, TP-VIB utilizes three multi-layer perceptron to construct a feature extractor $f_\theta$ for learning latent representations:

$$h_i = \ f_\theta(e_i; w_\theta, b_\theta), \quad i = 1, 2, ..., n \tag{1}$$

where $h_i$ is the corresponding representation of $e_i$. $w_\theta$ and $b_\theta$ denote the weight matrix and the bias matrix of the feature extractor in the representation learning network, respectively.

Then, TP-VIB conductes a classifier $g_\varphi$ based on a single-layer perceptron and the Softmax function to map representations into the target space for obtaining turnover prediction of employees:

$$\bar{p}_i = \ g_\varphi(h_i; w_\varphi, b_\varphi), \quad i = 1, 2, ..., n \tag{2}$$

$$p_i = \frac{\exp(\bar{p}_i)}{\sum_j \exp(\bar{p}_j)}, \quad i = 1, 2, ..., n \tag{3}$$

where $p_i$ is the corresponding turnover prediction of $e_i$. $w_\varphi$ and $b_\varphi$ denote the weight matrix and the bias matrix of the classifier in the pattern mining network, respectively. $exp(\cdot)$ stands for the exponential function.

### 2.2. The loss function

The task of employee turnover prediction aims to learn a low-dimensional representations $H$ that captures as much information about the target labels $Y$ as possible, which is achieved by maximizing the mutual information between $H$ and $Y$:

$$\max_{\varphi} I(H; Y) \tag{4}$$

Meanwhile, many raw data may contain noise, redundancy, or irrelevant features, all of which can interfere with the model's learning process, leading to decreased performance or reduced training efficiency. Thus, an intuitive and valuable mutual information restriction between data $E$ and representations $H$, i.e., $I(E; H) \leq I_c$, is obtained where $I_c$ stands for a constraint.

$$\max_{\varphi,\theta} I(H; Y) \quad s.t. \quad I(E; H) \ \leq I_c \tag{5}$$

Based on Lagrangian function optimization, Eq. 4 can be rewritten as:

$$\max_{\varphi,\theta} I(H; Y) - \alpha I(E; H) \tag{6}$$

where $\alpha$ stands for the Lagrange multiplier. The aforementioned loss function is commonly referred to as the information bottleneck [20]. The first term encourages representations $H$ to express labels $Y$ as much as possible and the second term encourages representations $H$ to compress data $E$ as much as possible. The two components seamlessly collaborate to enhance the model's ability in extracting robust and meaningful patterns while ensuring a balance between information preservation and compression.

Rooted in the concept of mutual information, TP-VIB leverages variational inference to derive a lower bound on the information bottleneck objective, aiming to optimize representation learning and pattern discovery networks. Specifically,

$$\begin{aligned} I(H; Y) = \int dydhp(y, h) \log \frac{p(y, h)}{p(y)p(h)} = \\ \int dydhp(y, h) \log \frac{p(y|h)}{p(y)} \end{aligned} \tag{7}$$

From the Markov Chain $Y \to E \to H$, $p(y|h)$ has:

$$p(y|h) = \int dep(e, y|h) = \int de \frac{p(y|e)P(h|e)p(e)}{p(h)} \tag{8}$$

Obviously, $p(y|h)$ is intractable. $q(y|h)$ is introduced as the variational approximation to $p(y|h)$ via minimizing Kullback Leibler divergence. It is obvious that:

$$KL(p(y|h)||q(y|h)) \geq 0 \tag{9}$$

Then, having:

$$\begin{aligned} I(H;Y) &\geq \int dydhp(y,h)\log q(y,h) - \int dyp(y)\log p(y) \\ &= \int dydhp(y,h)\log q(y|h) + H(Y) \end{aligned} \tag{10}$$

where $H(Y)$ stands for entropy of labels that is unrelated to optimization. Meanwhile, the joint distribution $p(E,H,Y)$ is written as:

$$\begin{aligned} p(E,H,Y) &= P(H|E,Y)P(Y|E)P(E) \\ &= P(H|E)p(Y|E)P(E) \end{aligned} \tag{11}$$

Hence, the lower bound of $I(H,Y)$ is defined as:

$$I(H;Y) \geq \int dedydhp(e)p(y|e)p(h|x)\log q(y|h) \tag{12}$$

Considering mutual information $I(E;H)$:

$$\begin{aligned} I(E;H) &= \int dedhp(e,h)\log\frac{p(h|e)}{p(h)} = \\ &\int dedhp(e,h)\log p(h|e) - \int dhp(h)\log p(h) \end{aligned} \tag{13}$$

Since it is intractable to compute the marginal distribution $p(h) = \int dep(h|e)p(e)$, a prior distribution $r(h)$ is introduced as variational approximation to $p(h)$. Similarly,

$$\begin{aligned} &KL(p(h)||r(h)) \geq 0 \Rightarrow \\ &\int dhp(h)\log p(h) \geq \int dhp(h)\log r(h) \end{aligned} \tag{14}$$

Thus, the upper bound of $I(E,H)$ is defined as:

$$I(E;H) \leq \int dedhp(e)p(h|e)\log\frac{p(h|e)}{r(h)} \tag{15}$$

Hence, the lower bound on the information bottleneck objective is rewritten as:

$$\begin{aligned} &\max_{\varphi,\theta} I(H;Y) - \alpha I(E;H) \\ &\geq \int dedydhp(e)p(y|e)p(h|x)\log q(y|h) \\ &- \alpha \int dedydhp(e)p(y|e)p(h|x)\log q(y|h) = L_{IB} \end{aligned} \tag{16}$$

To obtain a numerical solution of $L_{IB}$, the Monte Carlo sampling and the reparameterization trick are used in the experiments. Specifically, the empirical data distribution $p(e,y)$ is obtained via:

$$p(e,y) = \tfrac{1}{n}\sum_{i=1}^{n}\xi_{e_i}(e)\xi_{y_i}(y) \tag{17}$$

which is used to approximate $p(e)p(y|e)$. And $p(h|e)dh$ is approximated as $p(\varepsilon)d\varepsilon$ where $h = f(e,\varepsilon)$ and $\varepsilon$ stands for Gaussian random variable.

$$\mathcal{N}(h|f_\theta^\mu(e), f_\theta^\Sigma(e)) = p(\varepsilon)d\varepsilon \tag{18}$$

Having:

$$\begin{aligned} L_{IB} &\approx \frac{1}{n}\sum_{i=1}^{n} E_{\varepsilon\sim p(\varepsilon)}[\log q(y_i|f(e_i,\varepsilon))] \\ &- \alpha KL(p(h|e_i), r(h)) \end{aligned} \tag{19}$$

Furthermore, due to the imbalance between positive and negative samples in employee turnover prediction, TP-VIB introduces an entropy regularization term $L_{HR}$ to ensure that the model does not overfit to a specific cluster and overlook other potential structures in the data. This prevents all instances from being allocated to a single class, enhancing the model's generalization ability and robustness. It is shown as follows:

$$L_{HR} = \sum_{k=1}^{K} q_k \log q_k, \quad q_k = \tfrac{1}{n}\sum_{i=1}^{n} p_{ik} \tag{20}$$

When all samples are partitioned into a single class $k$, it signifies that $p_{ik} = 1, i = 1,2,...,n$ such that $q_k log(q_k) = 0$. When $0 \leqslant p_{ik} \leqslant 1$, having

$$q_k \log q_k \leq 0 \tag{21}$$

$L_{HR}$ enforces more samples to be partitioned into greater-than-zero rows in $P$.

In summary, the overall loss $L$ of TP-TIB, which is used to optimized the representation learning network and the pattern mining network rooted in SGD, is elaborated:

$$L = L_{IB} + \beta L_{HR} \tag{22}$$

Where $\beta$ is a balance parameter between $L_{IB}$ and $L_{HR}$. The final turnover prediction of TP-VIB is computed via:

$$\bar{y}_i = \arg\max(p_i), i = 1,2,...,n \tag{23}$$

where $\bar{y}_i$ stands for the turnover prediction of the $i$-th employee.

## 3. Experiments

### 3.1. Setup

**Dataset and metric**: The prediction performance of the TP-VIB in employee attrition for human resource management is evaluated with HR-Employee-Attrition dataset provided by IBM. It contains 14999 IBM employees with behavioral data of satisfaction_level, last_evaluation, number_project, average_montly_hours, time_spend_company, work_accident, promotion_5years, sales, salary, and left. Consistent with previous works, four metrics, i.e., Accuracy, Recall, F1-score, and Precision, are used to show superiority of TP-VIB in employee attrition in human resource management.

**Table 2.** Comparison results of TP-VIB to baselines on HR-Employee-Attrition dataset.

| Method | Accuracy | Recall | F1-score | Precision |
|---|---|---|---|---|
| RF | 0.893± 0.001 | 0.773± 0.003 | 0.839± 0.002 | 0.917± 0.003 |
| XGB | 0.812± 0.001 | 0.751± 0.003 | 0.828± 0.002 | 0.866± 0.005 |
| LR | 0.806± 0.002 | 0.646± 0.005 | 0.705± 0.003 | 0.776± 0.006 |
| NB | 0.644± 0.003 | 0.729± 0.006 | 0.596± 0.002 | 0.504± 0.003 |
| DT | 0.848± 0.001 | 0.795± 0.004 | 0.790± 0.002 | 0.785± 0.003 |
| GBDT | 0.891± 0.001 | 0.769± 0.003 | 0.835± 0.002 | 0.914± 0.004 |
| DeepWalk | 0.901± 0.007 | 0.813± 0.001 | 0.845± 0.001 | 0.924± 0.005 |
| DBGE | 0.937± 0.001 | 0.935± 0.001 | 0.938± 0.002 | 0.942± 0.003 |
| SDNE | 0.929± 0.002 | 0.903± 0.002 | 0.945± 0.007 | 0.933± 0.003 |
| MLT | 0.887± 0.003 | 0.869± 0.002 | 0.871± 0.002 | 0.900± 0.004 |
| DA-KNN | 0.911± 0.001 | 0.899± 0.001 | 0.917± 0.002 | 0.916± 0.002 |
| TP-VIB | 0.972± 0.001 | 0.962± 0.001 | 0.949± 0.001 | 0.975± 0.001 |

**Implementation Details**: We meticulously configured the key parameters for the deep learning model TP-VIB to ensure the effectiveness of the experiments and the reliability of the results. The number of training epochs was set to 200, a value validated through extensive experimentation to ensure adequate model learning while avoiding overfitting. The learning rate was established at 1e-4, a widely accepted starting point in the field of deep learning that facilitates rapid initial convergence of the model. The encoding dimension K was set to 256, representing the model's representational capacity in the latent space, balancing expressiveness with computational resources. A random seed of 1 was assigned to ensure the reproducibility of the experiments, maintaining consistent initialization states across all trials. The number of samples averaged for multi-epoch predictions was set to 12, which helps reduce the variance in prediction results and enhances the stability and accuracy of the model's predictions. The batch size was determined to be 100, striking a balance between memory usage and computational efficiency, ensuring the high performance of model training. The rational selection of these parameters is crucial for achieving optimal model performance and provides a solid foundation for subsequent analysis and improvement.

### 3.2. Comparison with baselines

**Comparison methods**: Nine baselines of employee attrition predictions in human resource management are used in the experiments, including Random Forest (RF), XGBoost (XGB), Logistic Regression (LR), Naive Bayes (NB), Decision Tree (DT), Gradient Boosting Decision Tree (GBDT), DeepWalk [21], DBGE [16], MLT [8], DA-KNN [6], and SDNE [22].

**Comparison results**: Table 2 exhibits a comparison outcomes regarding four metrics on HR-Employee-Attrition dataset. It is evident that TP-VIB outperforms all current baselines in terms of employee attrition prediction task, which proves effectiveness and superiority of information bottleneck loss and entropy regularization loss within deep frameworks. The seasons are twofold: (1) TP-VIB leverages the information bottleneck loss, which effectively balances between preserving the predictiveness of data representations and reducing unnecessary information redundancy. By finding a balance point and encouraging the model to learn more compact and meaningful data representations, TP-VIB enhances the model's generalization ability and prediction accuracy on unseen data. This mechanism ensures that the model focuses on extracting the most salient information related to turnover while filtering out irrelevant noise or distractions. (2) TP-VIB incorporates an entropy regularization term to address class imbalances in employee turnover datasets. This term helps balance the representation of positive and negative classes, thereby improving the robustness and generalization capability of the model. By introducing this regularization technique, TP-VIB effectively mitigates the impact of imbalanced data distributions, ensuring that the model can accurately predict both positive and negative instances of turnover. This results in a more reliable and practical solution for employee attrition prediction, ultimately leading to superior performance compared to current baselines.

Furthermore, there are two additional observations: (1) The prediction performance based on deep learning methods, e.g., SDNE and DBGE, is superior to that based on machine learning methods, e.g. XGB and DT, which reveals the powerful capability of deep learning in handling complex patterns of HR-Employee-Attrition datasets. (2) TP-VIB shows significant advantages in current deep learning based attrition prediction methods. The principle of the information bottleneck enhances the model by introducing a bottleneck layer, which encourages the model to learn more compact and informative feature representations. This design helps to improve the efficiency of data

**Table 3.** Ablation experiments of each loss in TP-VIB

| $I(H;Y)$ | $I(E;H)$ | $L\_HR$ | Accuracy | Recall | F1-score | Precision |
|---|---|---|---|---|---|---|
| √ | | | 0.603± 0.004 | 0.520± 0.013 | 0.627± 0.008 | 0.622± 0.010 |
| | √ | | 0.872± 0.001 | 0.869± 0.004 | 0.862± 0.003 | 0.869± 0.004 |
| √ | √ | | 0.954± 0.001 | 0.943± 0.003 | 0.939± 0.002 | 0.925± 0.001 |
| | √ | √ | 0.702± 0.007 | 0.651± 0.008 | 0.728± 0.005 | 0.761± 0.005 |
| √ | | √ | 0.902± 0.002 | 0.901± 0.002 | 0.928± 0.002 | 0.904± 0.004 |
| √ | √ | √ | 0.972± 0.001 | 0.962± 0.001 | 0.949± 0.001 | 0.975± 0.001 |

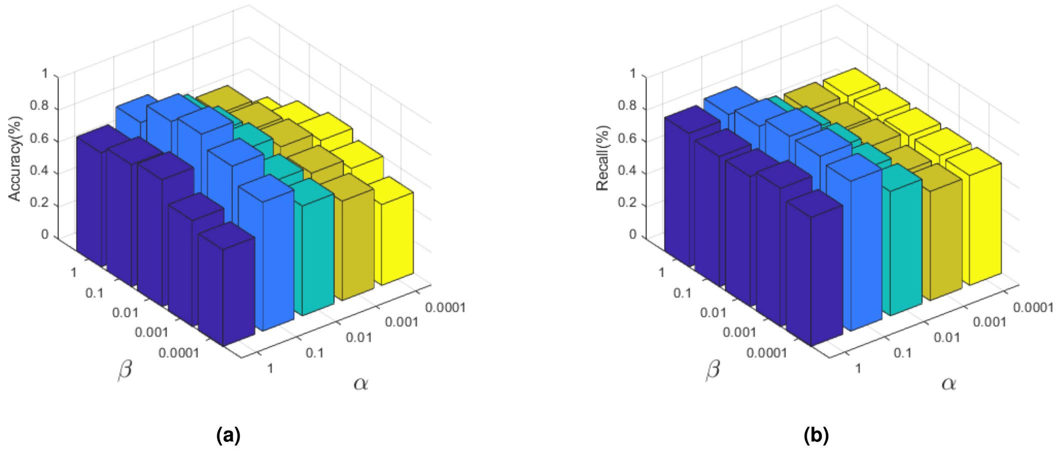


**Fig. 2.** The sensitivity analysis of parameters $\alpha$ and $\beta$ about Accuracy and Recall in TP-VIB.

compression because it reduces the dimensionality of the data while preserving the essential information crucial for completing the task.

### 3.3. Ablation Study

This section conducts five ablation experiments to further analyze loss effectiveness. Specifically, (1) TP-VIB maximizes $I(H;Y)$ to optimize representation learning and pattern mining networks for obtaining turnover predictions of employees. (2) TP-VIB minimizes $I(E;H)$ to optimize representation learning and pattern mining networks for obtaining turnover predictions of employees. (3) TP-VIB maximizes $I(H;Y)$ and minimizes $I(E;H)$ to optimize representation learning and pattern mining networks for obtaining turnover predictions of employees. (4) TP-VIB minimizes $I(E;H)$ and $L\_HR$ to optimize representation learning and pattern mining networks for obtaining turnover predictions of employees. (5) TP-VIB maximizes $I(H;Y)$ and $L\_HR$ to optimize representation learning and pattern mining networks for obtaining turnover predictions of employees.

As shown in Table 3, we can make three observations: 1. The importance of maximizing mutual information between representation and labels: When maximizing mutual information $I(H;Y)$, the model's predictive performance significantly improves, as seen in the first and third rows of the table. This suggests that optimizing the relationship between the representation and labels is crucial for accurate employee turnover predictions. 2. The role of minimizing mutual information between representation and input data: Minimizing mutual information $I(E;H)$ has a positive effect on model performance, but not as significant as when maximizing $I(H;Y)$. This indicates that while reducing the influence of noise and irrelevant features is helpful, it is more important to capture information relevant to the prediction target. 3. The dual role of the loss function $L_{HR}$: The loss function $L_{HR}$ plays a significant role in model performance optimization. While it can enhance model performance in some cases, it is not always necessary. The loss function is most effective when combined with other optimization objectives, as seen in the third row of the table.

### 3.4. Parameter Analysis

Parameter Analysis is conducted in terms of $\alpha$ and $\beta$ of TP-VIB on HR-Employee-Attrition dataset. Specifically, $\alpha$ and $\beta$ are constrained in $\{0.0001, 0.001, 0.01, 0.1, 1\}$. The results in Figure 2 show performance changes of TP-VIB with $\alpha$ and $\beta$. The results reveal insightful trends regarding the behavior of TP-VIB with respect to changes in $\alpha$ and $\beta$. Notably, when both $\alpha$ and $\beta$ are set to 0.1 and 0.01, respectively, TP-VIB achieves the best performance across all metrics. This observation suggests that a balanced value for these parameters allows the model to effectively integrate the contributions from both information bottleneck loss and entropy regularization loss within deep frameworks, leading to an optimal combination of classification accuracy and representation learning.

## 4. Conclusion

In this paper, a deep variational information bottleneck is proposed for modeling employee turnover prediction in human resource management. The information bottleneck objective is constructed using variational inference to establish a lower bound, and unbiased estimates of gradients are obtained through reparameterization techniques and Monte Carlo sampling, enabling the use of stochastic gradient descent to optimize the representation learning network and pattern mining network. Additionally, an entropy regularization term is introduced to address the imbalance between positive and negative classes. Finally, a series of experiments demonstrate that the stochastic neural networks trained with TP-VIB exhibit robustness against overfitting. Looking ahead, future work could explore several promising directions. Firstly, investigating the applicability of TP-VIB in other domains beyond human resource management could provide valuable insights into its generalizability and effectiveness. Secondly, extending TP-VIB to handle additional sources of data, such as textual or temporal data, could further enhance its predictive capabilities. Overall, these potential future directions hold promise for advancing the state-of-the-art in employee turnover prediction and related fields.

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