Multi-Relational Graph Neural Networks Based Model Prediction for Subjective Well-Being of Middle-aged and Elderly People

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Abstract. happiness is the basis for measuring the mental health and quality of life of middle-aged and elderly people. Traditional research methods based on machine learning models are low complexity and poor universality, leading to inaccurate results, deep learning convenient structural information among multiple relationships, which is conducive to improving the accuracy of happiness prediction. In this paper, we propose DL-GNN, a Multi-Relational Graph Neural Networks based Subjective Well-Being prediction model for middle-aged and elderly people. First, based on the CHARLS dataset, we construct the relational graph structure of the Subjective Well-Being of middle-aged and elderly people in terms of life satisfaction and depression; Second, we use a combination of Fully-Connected Network and Linear Regularization method to calculate the similarity of labels between nodes and select the similarity neighbor by neighbor sampling and similarity adaptive measurement to Finally, the attention mechanism is introduced to aggregate all the neighbor information within and between relations respectively, and the representation of target nodes is obtained through the layer-by-layer embedding between relations, which finally completes the construction of the DL-GNN model. The experiments show that the F1 score of DL-GNN model is 90.25% on the CHARLS dataset, the F1 score was improved by 4.78%,8.71%,10.93%and14.11% when compared with SDCN, GCN, XGBoost, and MLP, respectively.

Keywords: Middle-aged and Elderly; Subjective Well-Being; Deep Learning; Multi-Relational Graph Neural Networks; Prediction

1 Introduction

China has entered the stage of moderate aging [1], and according to the latest population data from the National Bureau of Statistics 2023, 19.8% of the population aged 60 years and above and 14.9% of the population aged 65 years and above were living in China by the end of 2022. Improving the happiness of middle-aged and elderly people is an important tool to solve the aging problem. It is of practical importance to improve the quality of life of middle-aged and elderly people by analyzing and predicting to grasp and understand the current overall level of Subjective Well-Being of middle-aged and elderly people, and to understand the overall mental status and psychological health of middle-aged and elderly people.

Happiness is a practical assessment of the objective state of life and a value-based assessment of the subjective meaning of life. Psychologists refer to the investigation of factors that influence

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people's positive or negative emotions and life experiences as "Subjective Well-Being"[2], Where the term " Subjective " refers to the researcher's assessment of the Subjective Well-Being through the judgmental information provided by the respondents, such as experiments, questionnaires, etc. Among the definitions of Subjective Well-Being, Diener et al [3] have the most representative and accepted definition, suggesting that Subjective Well-Being is the result of evaluating the quality of one's life according to one's own subjectively set criteria, and consists of four dimensions: life satisfaction, evaluation of various aspects of life, positive emotions, and negative emotions. Huajian Cai et al [4] consider the cognitive side of Subjective Well-Being: life satisfaction, also the affective side of Subjective Well-Being: positive and negative emotional experiences of the individual, in their judgments of Subjective Well-Being. Effective mining of information in Subjective Well-Being and its analysis and prediction is an important research problem for interdisciplinary applications.

Currently, the traditional methods based on machine learning models in existing studies can overfit noisy classification problems and have poor accuracy in predictive analysis of complex nonlinear relationships between input data (samples) and output data (labels). Compared with traditional machine learning methods, deep learning methods have better performance in modeling and analysis of nonlinear relationships, and thus are widely used in predictive analysis. In this paper, we propose a DL-GNN model based on a Multi-Relational Graph Neural Networks for the Subjective Well-Being data analysis required for middle-aged and elderly people to study happiness from the perspective of the importance of different relationships, to obtain the best prediction results.

2 Related Work

Psychological factors have been found to have some weight in the predictors of happiness, such as stress coping methods [5], perceived social support [6], or personality [7], while most of the traditional studies have used multiple linear regression (MLR) [8] for happiness prediction. Haruna Danladi Musa [9] stated that the level of community happiness depends on the existing level of urban sustainability. CH-index planners provide a new Subjective Well-Being tool that allows for better-targeted interventions to improve baseline data on community happiness. Saputri et al [10] state that happiness factors vary depending on individual's perspective. The factors used in this work include both material and spiritual human needs and use Support vector machine (SVM) machine learning techniques to learn and predict cross-country differences in happiness factors. Francisco Javier Pérez-Benito et al [11] used a data structure-driven architecture of deep neural networks to define a predictor of happiness, capturing the conceptual structure of the predicted happiness level by standardizing the psychological variables assessed by the questionnaire and extracting the factors that have a more significant impact on the results. Haoge Ding et al [12] proposed a graphical convolutional neural network-based trend prediction of teacher happiness, which provides a comprehensive analysis of factors affecting teacher happiness in terms of academic innovation, job satisfaction, and student development rate.

For happiness, traditional machine learning methods mostly use individual feature hypotheses for data analysis and are unable to obtain prediction results through the collective level. To address this issue, this paper uses cognitive and affective dimensions as evaluation indicators of Subjective Well-Being of middle-aged and elderly people, DL-GNN model was proposed to predict the Subjective Well-Being of middle-aged and elderly people using a multi-relational graph neural network, which effectively expresses the correlations between nodes, extracts the relevant features of nodes, and improves the prediction accuracy.

3 Subjective Well-Being of Middle-aged and elderly people prediction model DL-GNN

3.1 Multi-Relational Graph definition

A Multi-Relational Graph is defined as $G=\{\mathcal{V}, X, E_S, Y\}$, where $\mathcal{V}$ is the set of node $\{v_1,...,v_n\}$,n is the number of nodes. X is the set of node features $X=\{x_1,...,x_{.n}\}$, The d-dimensional characteristic relationship matrix is calculated as $W_s \in \mathbb{R}^{d' \times d}$. E is the set of edges and E_s is the relation $s \in \{1,...,S\}$ that exists between two nodes, where s is the number of relation, and an edge can contain multiple types of relation. Y is the set of labels for $\mathcal{V}$ nodes, Which $Y=\{0,1\}$,1 represents happiness, and 0 represents unhappiness.

3.2 Multi-Relational Graph Neural Networks

Graph neural networks (GNNs) [13] are a deep learning framework that embeds graph-structured data by aggregating information from its neighboring nodes. However, when facing Multi-Relational Graphs, the complexity and diversity of edges in the graph need to be considered. According to the different relations outlined from the perspective of multi-layer neighbor aggregation, different relations s in the central node v will neighbor representation for aggregation, the hypothesis that l represents the number of layers:

$$\mathrm{h}_{v,s}^{(l-1)} = \mathrm{AGG}_s^{l-1}\left\{(\mathrm{W}_s \mathrm{h}_{v',s}^{l-1}) : (v, v') \in E_{v,s}^{(l)}\right\} \tag{1}$$

$$\mathrm{h}_v^l = \sigma(\mathrm{W}_s \mathrm{h}_v^{l-1} \oplus \mathrm{AGG}^l\left\{\mathrm{h}_{v,s}^{l-1} : s \in S\right\}) \tag{2}$$

Eq. (1) first aggregates the neighbors embedded within each relation, where $E_{v,s}^{(l)}$ is the set of edges under the aggregation of all nodes v and all neighbors v' l-1th layer relation s. $\mathrm{h}_{v',s}^{l-1}$ is the d-dimensional feature vector under the relation s at the l-1th layer. AGG is the aggregation function, AGG_s^{l-1} maps the neighborhood information of relation s under the l-1th layer into a single vector. Eq. (2) aggregates the relation graph of node v between relation s, σ denotes the activation function, $\oplus$ represents the operator, Combine the information of node v with the information of its neighbors. $\mathrm{h}_v^{(0)}$ for initializing embedded nodes, the node embedding representation of the nodes is obtained by aggregating the relation layer by layer, and the node embedding at the last layer yields the prediction results. Thus, the Multi-Relational Graph Neural Networks aggregates the embedded representations under each relation once again.

3.3 Similarity Neighbor Node Selector

In traditional graph neural network models for prediction studies some neighboring nodes with noise cannot filter the information effectively, which leads to the influence on the aggregation results of the central node v during the node aggregation process. In the relation graph defined in this paper, for the central node $\mathrm{v}\left(v \in V\right)$,inspired by GraphMix[14],the Fully-Connected Network(FCN) is used to enhance the graph neural network regularization training as a labeled node predictor to caculate the simi arity between the central node v and all neighbors v'under the l -1th layer relation, $S^{(l)}\left(v, v'\right)$ is the similarity between two nodes is calculated as follows eq.(3):

$$S^{(l)}\left(v, v'\right)=\frac{(\sigma(FCN^{(l)}(h_{v}^{(l-1)})))^{T}(\sigma(FCN^{(l)}(h_{v}^{(l-1)})))}{\left\|(\sigma(FCN^{(l)}(h_{v}^{(l-1)})))^{T}\right\|_{2}\left\|(\sigma(FCN^{(l)}(h_{v}^{(l-1)})))\right\|_{2}} \tag{3}$$

Where σ denotes the nonlinear activation function, $h^{(l-1)}$ denotes the input l -1th layer embedding, and $\mathrm{h}_{v}^{(l-1)}$ when the l -1th layer embedding node. The parameters of the model are adjusted to better fit the relation between the labels and the predicted values by comparing some known labels and the corresponding FCN predictions and calculating the cross-entropy loss between them to be used to update the similarity metric parameters. Define the cross-entropy loss of a single-layer FCN as shown in eq.(4):

$$\mathcal{L}_{simi}^{l}=\sum_{v \in \mathcal{V}}-\log(y_{v} \cdot \sigma(FCN^{l}(h_{v}^{l}))) \tag{4}$$

where $y_{v} \in Y$ denotes the set of labels of the central node v.

For each central node v processed under different relation s , $top - p$ sampling, and adaptive filtering thresholding are used to construct similar neighbors.

3.4 Neighbor Relation Aggregator

There are two ways to aggregate neighbor representations based on different relation s in the central node v. There are intra-relation aggregation and inter-relation aggregation.

Intra-relation aggregation: in each relational graph, the central node has multiple neighbor nodes, and it is necessary to process the information of each neighbor node separately and aggregate them by introducing an attention mechanism and deriving eq.(5) according to eq.(1):

$$\mathrm{h}_{v,s}^{(l)}=\left\{\sum_{(\mathrm{v},\mathrm{v}') \in \mathrm{E}_{v,s}^{l-1}} a_{v'}^{s}(\mathrm{W}_{s}\mathrm{h}_{v',s}^{l-1}) \mid (v, v') \in \mathrm{E}_{s,r}^{l-1}\right\} \tag{5}$$

where $a_{v'}^{s}$ is denoted as the weight coefficient as shown in eq. (6) and (7):

$$\alpha_{v'}^{s}=att_{\alpha}^{s} * \left[\mathrm{h}_{v,s}^{l-1} \,\|\, \mathrm{h}_{v',s}^{l-1}\right] \tag{6}$$

$$\alpha_{v'}^{s}=\frac{\alpha_{v'}^{s}}{\sum_{(v,v') \in E_{v,s}^{l-1}} \alpha_{v'}^{s}} \tag{7}$$

where $\left|E_{v,s}^{l-1}\right|$ denotes the number of all neighbor nodes of the central node v of the l -1th layer relation s , $||$ denotes the connection character.

Inter-relation aggregation: aggregating the updated information of the central node v in multiple relationship graphs and aggregating them by introducing an attention mechanism, as shown in eq. (8) derived according to (2):

$$\mathrm{h}_v = \sigma\left(\mathrm{W}_v \mathrm{h}_v^{l-1} \oplus \sum_{s\in S} p_v^s \mathrm{h}_{v,s}^l\right) \tag{8}$$

where p_v^s is the weight factor, As shown in eq. (9) and (10):

$$\beta_v^s = att_\beta^s * \left[\mathrm{h}_v^{l-1} \,||\, \frac{\mathrm{h}_{v,s}^l}{|S|}\right] \tag{9}$$

$$p_v^s = soft\max\left(\beta_v^s\right) = \frac{\beta_v^s}{\sum_{s\in S} \beta_v^s} \tag{10}$$

where $|S|$ denotes the number of relation.

For each central node v ,after aggregation in both intra-relation and inter-relation ways, the final layer outputs $z_v = \mathrm{h}_v^{(L)}$ as its final embedding and defines the loss of TOG as a cross-entropy loss function as shown in eq.(11) below:

$$\mathcal{L}_{TOG} = \sum_{v\in V} -\log(y_v \cdot \sigma(MLP(\mathrm{z}_v))) \tag{11}$$

Therefore, finally loss function of the entire model is defined, as shown in eq.(12) below:

$$\mathcal{L}_{DL} = \mathcal{L}_{TOG} + \lambda_1 \mathcal{L}_{simi} + \lambda_2 \left\|\Theta\right\|_2 \tag{12}$$

where λ_1 and λ_2 are denoted as weight parameters, $\left\|\Theta\right\|_2$ is denoted as the weight parameter of the model.

3.5 DL-GNN Model

In this paper, we use the relational attributes and feature representation capabilities in graph neural networks to construct models. First, four specific relations age, positive factors, negative factors, and life satisfaction in the CHARLS dataset are selected to construct a multi-relational map of the Subjective Well-Being of middle-aged and elderly people. Second, a combination of a fully connected neural network and linear regularization method is used as a labeled node predictor to calculate the similarity of node labels and neighbor selection is performed by neighbor sampling and similarity adaptive measurement to filter the neighbor nodes with low similarity of the central node, and the neighbor nodes with higher similarity are used in the multi-relational graph. Finally, the attention mechanism is introduced to aggregate all neighboring node information within and between relations to the central node, respectively, and the target node representation is obtained through layer-by-layer embedding, and the node embedding in the last layer yields the prediction results, which finally completes the construction of the DL-GNN model, as shown in Figure 1.

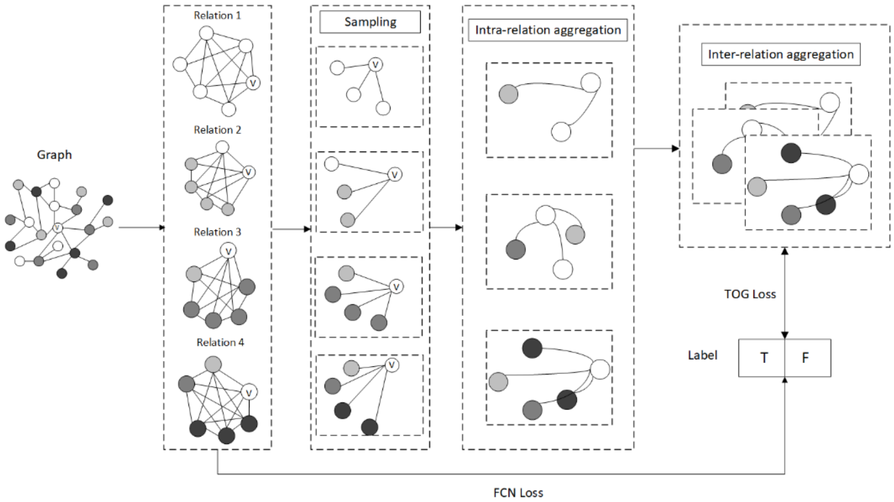


Fig. 1. DL-GNN architecture.

The Subjective Well-Being prediction task for middle-aged and elderly people is essentially a binary classification problem, and the final result is divided into two categories, with happiness denoted as 1 and unhappiness denoted as 0. The implementation process of the subjective well-being prediction method for middle-aged and elderly people based on Multi-Relational graph neural network is shown in Algorithm 1:

Algorithm 1: Multi-Relational Graph Neural Networks based algorithm for predicting the Subjective Well-Being of middle-aged and elderly people

Input: An undirected multi-relational graph: $G=\{\mathcal{V}, X, E_s, Y\}$,epochs: N ,Number of layers: L

Output: Finally z_v node embedding indicates, that the output result is happiness or unhappiness

1: $h_v^{(0)} \in x_v$, $v \in V$, $E_s^{(0)} = E$, $W_s \in \mathbb{R}^{d' \times d}$, $s \in \{1,...,S\}$ #Initialization
2: for $n = 1,...,N$ do #Start Training
3: for $l = 1,...L$ do
4: for $s = 1,...S$ do
5: $S^{(l)}(v, v') \rightarrow$ Eq. (4) # Similarity calculation
6: $E_s^{(l)}$ #top-p sampling builds similar neighbors
7: $h_{v,s}^{(l)} \rightarrow$ Eq. (6) #Intra-relation aggregation
8: end for
9: $\mathcal{L}_{simi}^{l} \rightarrow$ Eq. (5) # Cross-entropy loss of single-layer FCN
10: $h_v^{(l)} \rightarrow$ Eq. (9) #Intre-relation aggregation
11: end for
12: $z_v = h_v^{(L)}$ # Last layer node embedding representation

13: end for
14: Calculate the cross-entropy loss function $\mathcal{L}_{TOG}, \mathcal{L}_{DL}$
15: Parameter Update
16: return Prediction results

4 Experiment comparison and analysis

4.1 CHARLS data and research sample

The data for this study were obtained from the China Health and Retirement Longitudinal Study (CHARLS, 2011-2018), which included a nationally representative sample of 17,092 respondents aged 45 years and older in 28 provinces, people, using multistage probability sampling and face-to-face interview surveys. By studying and screening relevant questions in the questionnaire, multiple groups of these variables, including individual variables (gender, age, region, occupation, health, education, marital and political status, etc.) and family variables (parents, spouse, children, family, etc.).

4.2 Respondent relation definition

Subjective Well-Being was measured by positive and negative factors (depressive symptoms) and life satisfaction from the Depression Scale. Depressive symptoms were assessed using the Center for Epidemiologic Studies Depression Scale 10-item (CESD-10) [15]. In this paper, respondents with different labels are considered nodes, and 78 features of each respondent(C) are selected to construct a feature vector matrix, Four relation diagrams were formed based on age(A), positive factors(J), negative factors(X), and life satisfaction(V): 1) C-A-C: it connects respondents with the same age; 2) C-J-C: it connects respondents with the same positive factors; 3) C-X-C: it connects respondents with the same negative factors; 4) C-V-C: it connects respondents with the same life satisfaction.

4.3 Results and Discussion

In order to evaluate the model happiness prediction performance, comparative experiments were conducted using the multilayer perceptron (MLP), XGBoost [16], GCN [17], and SDCN [18] methods. As shown in Table 1, the values of XGBoost and MLP are improved by 10.93% and 14.11%, respectively, compared to DL-GNN, and GCN is improved by 2.22% compared to these two methods. The value of SDCN, a structural deep clustering network model, reaches 85.47%, which is relatively high. However, the highest is the DL-GNN model with a value of 90.25%

Table 1. Model performance comparison analysis table

Dataset	CHARLS			
Method	F1	Precision	AUC	Recall
MLP	0.7614	0.7892	0.7943	0.7726
XGBoost	0.7932	0.8135	0.8255	0.7989
GCN	0.8154	0.8382	0.8435	0.8575
SDCN	0.8547	0.8765	0.8865	0.8644
DL-GNN	**0.9025**	**0.9214**	**0.9331**	**0.9185**

In training the DL-GNN model for comparison with the benchmark model, this paper uniformly sets the number of iterations to 50, the ratio of the training set to test set to 6:4, the optimizer to Adam, the parameter learning rate to 0.01, the node embedding size to 64. the number of layers in the DL-GNN model is set to 1, the similarity loss value λ_1 to 2, and the regularization weight λ_2 to 0.001. Figure 2 shows the values of different models on the CHARLS dataset. DL-GNN model outperforms the benchmark models MLP, XGBoost, GCN, and SDCN in terms of F1-score as the number of training iterations increases.

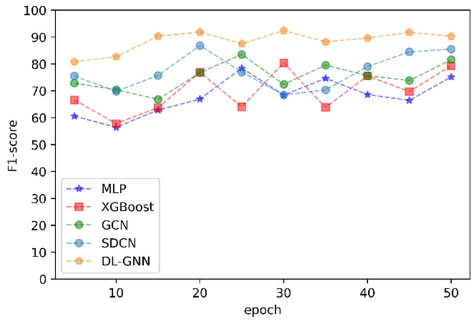
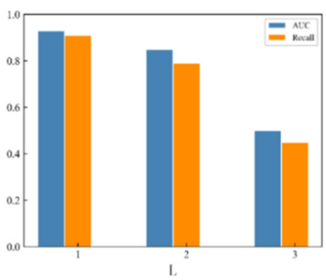


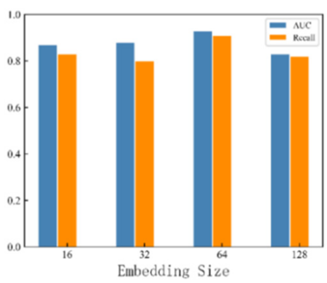
Fig. 2. Performance comparison of F1-score for different models

Figure 3 shows the performance of DL-GNN tested on the CHARLS dataset for four hyperparameters. In which the performance under different layers of the model is represented in Fig. 3(a), the best classification results are obtained for the single-layer model, and the DL-GNN model has an overfitting problem when the model is three layers. The effect of embedding size on the performance at 16, 32, 64, and 128 is indicated in Fig. 3(b), and the results are relatively stable when the embedding size is 64.

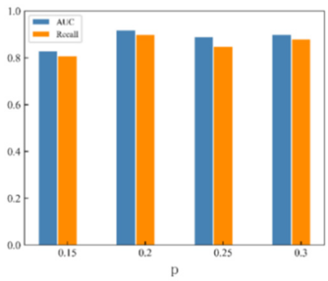
The performance of the model with different p ($Top-p$ neighbors) is illustrated in Figure 3(c), and the optimal result is to select the top 20% of neighbor nodes for aggregation. The effect of different λ_1 values on the weight of $\mathcal{L}_{Simi}^{l}$ is illustrated in Fig. 3(d), and the model achieves the best performance when the λ_1 value is 2.



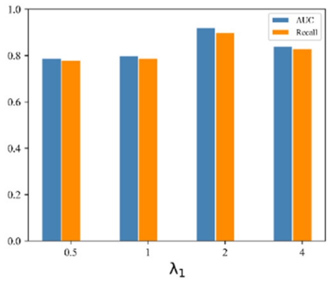
(a) Number of Layers



(b) Embedding Size



(c) *T*op-p neighbor



(d)Simi loss Weight

Fig. 3. Effect on results in different parameter configurations under 50 epochs

5 Conclusion

DL-GNN addresses the shortcomings of traditional machine learning methods and uses multi-relational graph neural networks as evaluation indicators to predict the Subjective Well-Being of middle-aged and elderly people. This method effectively addresses the information transfer between multiple relationships and captures the complex relationships between graph-structured data, thus improving the prediction results. By comparing with other traditional models, the DL-GNN model combines the advantages of deep learning, which can effectively provide the basis and decision on the Subjective Well-Being situation of middle-aged and elderly people, thus improving their quality of life.

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