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LETTER

A graph-based contrastive learning framework for medicare insurance fraud detection

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1 Introduction

With the improvement of people's living standards, medical insurance has gradually moved towards universal coverage in recent years. Nevertheless, problems such as medical insurance fraud, resource waste and drug abuse emerge successively, which cause a colossal waste of public resources. Therefore, reducing or eliminating medical insurance fraud can safeguard the medical insurance fund, which is essential for promoting economic development, improving public health, and maintaining social stability [1].

The specialized challenges for medical insurance fraud detection are summarized as follows:

- Expertise. To detect medicare insurance fraud, it involves strong medical expertise. However, clinical treatment is a complex professional behaviour. For different diseases, doctors will prescribe different medicines. It is almost impossible to sort out the massive correlations of medicines for insurance fraud detection by humans.
- Dynamic. The treatments of patients are varying along with time which is a dynamic process, consisting of various treatment records at different timestamps. The time intervals between records are unevenly distributed, which may reveal the rationality of therapeutic behaviors and become a very important signal to detect the insurance fraud.

To overcome the challenges, we propose a novel framework GCLF (Graph-based Contrastive Learning Framework) for medicare insurance fraud detection. In order to solve the expertise problem and model the complex relationships between medicines, we construct a medicine graph according to their co-occurring frequency. To capture the dynamic patterns of treatment procedures, we propose a self-supervised sequence model Self-Supervised LSTM. As shown in Fig. 1, according to diagnosis information, we construct positive and negative sample pairs according to the similarity level of two diagnosis information. We want to ensure the representations of similar diagnoses generated from the treatment sequence be more similar than the different diagnoses, so as to obtain better medicine representations by a self-supervised contrastive learning way.

2 Model

The overall architecture of the proposed model is shown as Fig. 2.

2.1 Problem formulation

The problem of medicare insurance fraud detection is defined as follows: Given a patient's treatments sequences $Tre^p = \left\{r_1^p, r_2^p, \ldots, r_n^p\right\}$ consisting of n treatment records, where $r_i^p = \left\{med_i^p, dos_i^p, price_i^p\right\}$, the corresponding related demographic of patient $Dem^p = \{age^p, gender^p, cat^p\}$ and diagnosis information $Dia^p = \{dis^p, dep^p, days^p\}$, we aim to assign a label $y_i^p \in \{0,1\}$ on record $r_t^p \in Tre^p$ to indicate whether the record commits a fraud or not (see Fig. 3).

2.2 Medicine graph construction

First, we count all the bigrams showing up simultaneously in all treatment sequences. For example, $med_{t_0}^p = m_1$, $med_{t_0}^p = m_2$,

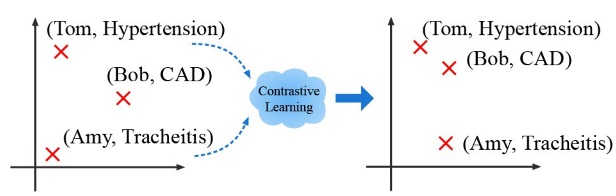

Fig. 1 Contrastive learning can enhance fraud detection performance by distinguishing dissimilar diagnosis and gathering similar diagnosis (e.g., CAD and Hypertension, both of which are a kind of cardiovascular disease)

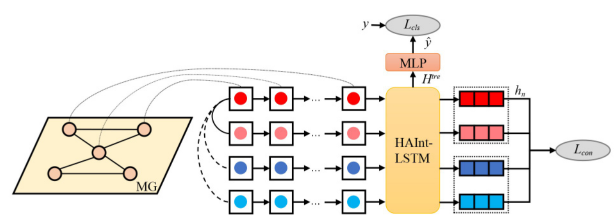

Fig. 2 The overall framework of our proposed model. And the dashed box indicates treatment procedures with similar diagnosis

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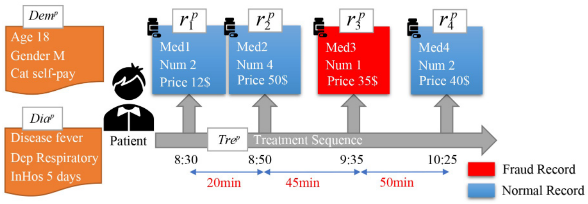

Fig. 3 Problem formulation of medicare insurance fraud detection

$med^p_{t_0} = m_3$, and $med^p_{t_1} = m_4$, which means that for patient p, doctor prescribe medicines m_1, m_2, m_3 at timestamp t_0 and m_4 at timestamp t_1. Then three medicine bigrams will be extracted: (m_1, m_2), (m_1, m_3) and (m_2, m_3). Second, we construct MG according to occurrence frequency of bigrams. Weight of the undirected edge can be computed by:

$$w\left(med_i, med_j\right) = \begin{cases} 1, & count\left(med_i, med_j\right) \geqslant \beta, \\ 0, & count\left(med_i, med_j\right) < \beta, \end{cases} \tag{1}$$

where $count\left(med_i, med_j\right)$ means the occurrence frequency of the bigram $\left(med_i, med_j\right)$ in the dataset.

The embeddings of medicines on MG are defined as follows:

$$X_{\mathcal{V}} = GCN(features, adj), \tag{2}$$

where $features$ denotes the initial features of medicines on graph (e.g., price and type of medicines), adj denotes the adjacency matrix of MG.

2.3 SS-LSTM

To discover dynamic dependencies among records and predict fraud record in treatment procedures, we model treatment procedures as sequences. Each record r_{t_i} is encoded by concatenating medicine embedding on graph, normalized price and normalized dosage as follows:

$$x_i = [X_{med_{t_i}}, num_{t_i}, price_{t_i}]. \tag{3}$$

In consideration of time interval, we employ part of HAint-LSTM [2] and improve it to a bi-directional model. Most structure of our recurrent unit is similar with LSTM, except the forget gate, which is defined as:

$$\overrightarrow{f_t} = \sigma\left(W_f\left[\overrightarrow{h_{t-1}}, x_t, \Delta T_{t-1,t}\right] + b_f\right), \tag{4}$$

where $\Delta T_{t-1,t}$ denotes the difference value between the timestamp of t-th record and the timestamp of $(t-1)$-th record. For simplicity, we denote each hidden state of the treatment record as $h_i \in R^{2u}$, and u is the size of the hidden state vector in HAint-LSTM:

$$h_i = \left[\overrightarrow{h}_i, \overleftarrow{h}_i\right]. \tag{5}$$

To better embed dynamic sequence for downstream fraud detection task, we propose to employ contrastive learning to introduce additional self-supervised signals. We follow the steps below:

- We sort all samples in training dataset according to their diagnosis information. And then we treat adjacent treatment sequences in the same batch as similar positive sample pairs, and nonadjacent pairs negative sample pairs.
- The sequence unit introduced above is employed as the encoder, and we embed the whole sequence as the last hidden state layer: $z_k = h^k_n$. The superscript k means the kth sample in minibatch.
- We formally define the contrastive loss between positive samples u and v as follows:

$$sim(u, v) = \frac{u^{\mathrm{T}} v}{|u||v|}, \tag{6}$$

$$\ell_{u,v} = -\log \frac{\exp\left(\mathrm{sim}\left(z_u, z_v\right)/\tau\right)}{\sum_{k=1}^{2N} \mathbb{I}_{[k \neq u]} \exp\left(\mathrm{sim}\left(z_u, z_k\right)/\tau\right)}, \tag{7}$$

where $\mathbb{I}_{[k \neq u]} \in \{0, 1\}$ is an indicator function evaluating to 1 iff $k \neq u$ and τ denoted a temperature.
- The final contrastive loss is the arithmetic mean of the loss of all positive sample pairs in the batch:

$$\mathcal{L}_{con} = \frac{1}{2N} \sum_{k=1}^{N} \left(\ell_{2k-1,2k} + \ell_{2k,2k-1}\right). \tag{8}$$

2.4 Training details

The classification cross entropy loss with regularization is defined as follows:

$$\mathcal{L}_{cls} = -\frac{1}{2N} \sum_{i=1}^{2N} \left[y_i \ln\left(y'_i\right) + (1 - y_i) \ln\left(1 - y'_i\right)\right] + \lambda \|\Theta\|_2^2, \tag{9}$$

$$\mathcal{L} = \alpha \mathcal{L}_{cls} + (1 - \alpha) \mathcal{L}_{con}, \tag{10}$$

where α is a hyperparameter to keep a balance between classification loss and contrastive loss.

3 Experiment

We conduct our experiments on real-world datasets, and the overall experiment results are shown in Table 1. In addition, statistical data information of the datasets is exhibited in Table 2. In each part, we sample 800 treatment sequences for training and 100 treatment sequences for testing. Besides, the ablation experiment results are shown in Table 3.

From the overall results, we can have the following observations:

- All sequential models achieve significantly better results than the traditional machine learning methods Linear Regression and Decision Tree. The main reason lies in the close contextual relationships between patient treatment procedures, which is critical in fraud detection.
- Comparison between TLSTM, VS-GRU, HAInt-LSTM and normal LSTM shows that the models that consider the uneven distribution of time between records perform better than the conventional sequence model. This confirms our conjecture about the importance of time intervals.
- Our proposed GCLF significantly outperforms all baseline methods in all datasets. The average

Table 1 Performances of different methods on the dataset

	Part I		Part II		Part III		Average	
	F1-score	AUC	F1-score	AUC	F1-score	AUC	F1-score	AUC
Linear regression	0.5412	0.7938	0.5309	0.7867	0.5250	0.7682	0.5324	0.7829
Decision tree	0.5723	0.8402	0.5541	0.8138	0.5531	0.8177	0.5589	0.8239
LSTM	0.7228	0.9788	0.7486	0.9833	0.7403	0.9850	0.7372	0.9824
ON-LSTM [3]	0.7521	0.9791	0.7661	0.9822	0.7582	0.9861	0.7588	0.9824
TLSTM [4]	0.7781	0.9743	0.7716	0.9809	0.7531	0.9778	0.7676	0.9777
VS-GRU [5]	0.7832	0.9748	0.7698	0.9812	0.7543	0.9745	0.7691	0.9768
HAInt-LSTM [2]	0.7854	0.9821	0.7642	0.9851	0.7783	0.9825	0.7760	0.9832
GCLF(ours)	**0.8686**	**0.9913**	**0.8889**	**0.9977**	**0.8866**	**0.9975**	**0.8813**	**0.9955**

Table 2 The statistical information of dataset

Dataset	Type	#Positive	#Negtive	#Positive rate
Part I	Training	4,726	118,302	3.84%
	test	501	14,312	3.38%
Part II	Training	4,732	118,032	3.85%
	test	514	14,541	3.53%
Part III	Training	4,862	119,812	3.90%
	test	541	13,989	3.72%

Table 3 F1-score of ablation test on the proposed GCLF

	Part I	Part II	Part III
GCLF	**0.8686**	**0.8889**	**0.8866**
-Medicine graph	0.7922	0.7867	0.7987
-Contrastive loss	0.8487	0.8657	0.8583

improvement over the best baseline method are 13.57% and 1.25% for F1 score and AUC, demonstrating its strong capability in learning record embeddings for medicare insurance fraud detection.

4 Conclusion

In this paper, considering the characteristics of fraud behaviours in medicare insurance, we propose a graph-based contrastive learning framework. We hope this paper can help to promote the security of the medicare insurance field.

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