A Graph-based Contrastive Learning Framework for Medicare Insurance Fraud Detection

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Frontiers of Computer Science, DOI: 10.1007/s11704-022-1734-0

Problems & Ideas

- Main Challenges:
  - **Expertise** To detect medicare insurance fraud, it involves strong medical expertise. However, clinical treatment is a complex professional behaviour.
  - **Dynamic** The treatments of patients are varying alone with time which is a dynamic process, consisting of various treatment records at different timestamps.
- Current Approaches:
  - Fail to properly model the data and are mainly based on machine learning
  - Ignore the information from the medical data itself
- Ideas:
  - **Medicine Graph** capture the strong correlations of different medicines
  - **Contrastive Learning** introduce self-supervised common sense: similar patients share similar treatment measures

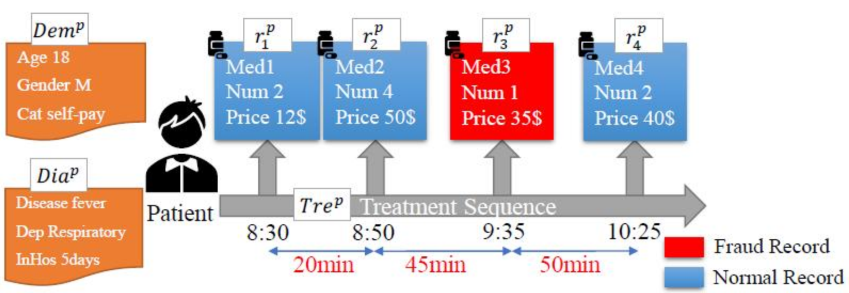

Fig.1:Problem formulation of medicare insurance fraud detection

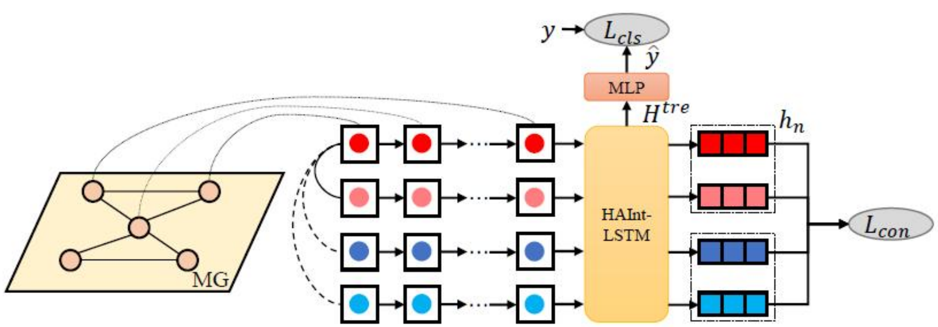

Fig.2: The overall framework of GCLF

Main Contributions

- Contributions:
  - Considering the characteristics of fraud behaviours in medicare insurance, we propose a graph-based contrastive learning framework. Experimental results on real-world datasets demonstrate the superiority of our method.
  - The proposal of medicine graph construction compensates for the lack of medical knowledge in the task.
  - The introduction of contrastive learning provides additional self-supervised knowledge and provides a high quality drug embedding for downstream tasks.

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**