Obstetric Diagnosis Assistant via Knowledge Powered Attention and Information-Enhanced Strategy

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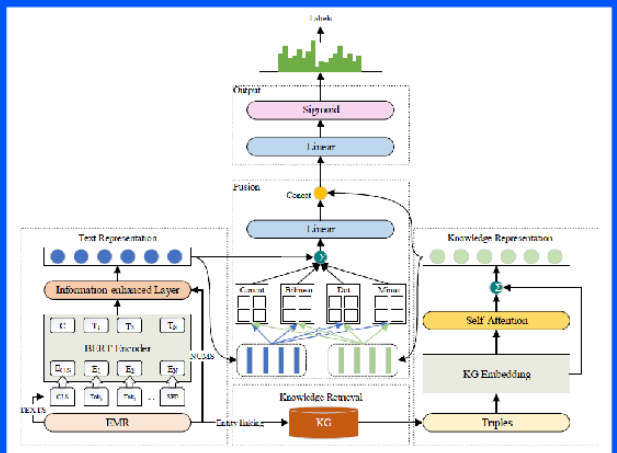

Fig. 1. The architecture of the KAIE model.

Model Architecture. Our proposed KAIE model is shown in Fig. 1. It can be divided into five parts: text representation generation module, knowledge retrieval module, knowledge representation module, fusion module, and the output module.

Knowledge Retrieval. The bi-directional matching method and similarity-based method are employed to obtain the entities in EMR and link to the KG.

$$score_l = \frac{|longestcommonsubsequence(e_i, k_j)|}{max(len(e_i), len(k_j))}$$

$$score_{final} = Average(score_L, score_J, score_l)$$

$$score_L = 1 - \frac{Levenshtein(e_i, k_j)}{max(len(e_i), len(k_j))}$$

$$score_J = jaccard(bigram(e_i), bigram(k_j))$$

Model

Text Representation Generation. We add the chief complaint information to the BERT input and use the numerical information by multi-head attention to enhance the text representation.

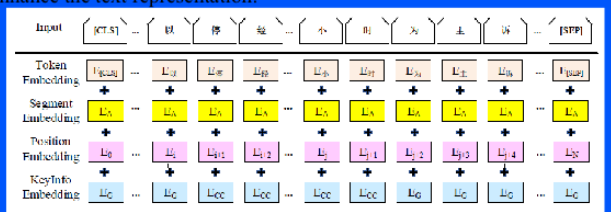

Fig. 2. The input embedding of the KAIE model.

$$Q = K = V = W^N Concat([C]; Num_1, \ldots, M)$$

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

$$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$$

$$[C'] = Concat(head_1, \ldots, head_h)W^O$$

Fusion. we further merge the text representation and knowledge representation using the multi-way attention mechanism.

Concat Attention

$$a_i = softmax(V_c^T(tanh(W_c^1[C'']_i + W_c^2 K_j'')))$$

$$[C'']_c = \sum_{i=1}^{N} a_i [C'']_i$$

Bilinear Attention

$$a_i = softmax([C'']_i^T W_b K_j''))$$

$$[C'']_b = \sum_{i=1}^{N} a_i [C'']_i$$

Dot Attention

$$a_i = softmax(V_d^T tanh(W_d([C'']_i \odot K_j''))),$$

$$[C'']_d = \sum_{i=1}^{N} a_i [C'']_i$$

Minus Attention

$$a_i = softmax(V_m^T tanh(W_m([C'']_i - K_i''))))$$

$$[C'']_m = \sum_{i=1}^{N} a_i [C'']_i$$

Final Output

$$[C'']_{final} = Concat(Concat([C'']_c; [C'']_b; [C'']_d; [C'']_m)W^{F1}; K'')$$

Experiments

Dataset.

Obstetric First Course Record Dataset. The first course records include 24,339 EMRs from multiple hospitals in China.

Knowledge Graph

COKG. The knowledge graph is shown on the right, the address is http://47.106.35.172:8088/

中文产科知识图谱COKG

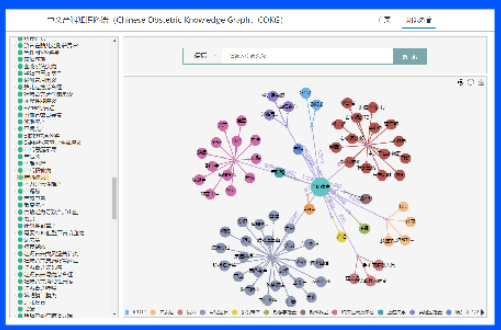

Table 1. The results on Chinese obstetric EMRs.

Model	F1(%)	P(%)	R(%)	HL(%)
CC	54.83	60.21	50.34	0.0306
RAKEL	59.68	63.87	56.01	0.0254
BiCRU	74.51	79.48	70.12	0.0243
CNN	76.72	80.65	73.17	0.0198
SGM	60.40	62.67	58.29	0.0200
BERT	79.74	80.63	78.87	0.0056
KAIE	**81.11**	**83.22**	**79.12**	**0.0051**

Table 2. The results of ablation studies.

Model	F1(%)	P(%)	R(%)	HL(%)
KAIE	81.11	83.22	79.12	0.0051
-N	80.99	81.84	80.16	0.0053
-KeyInfo	80.73	81.93	79.55	0.0053
-KG	80.87	83.23	78.64	0.0052

Conclusion

This paper propose a KAIE model for diagnosis assistant, which integrates the numerical information, chief complaint information, and external knowledge from COKG to improve the performance of diagnosis. In future research, we will integrate more public knowledge graphs and use more advanced knowledge graph embedding methods to further improve the diagnosis results.

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