

DKEC: Domain Knowledge Enhanced Multi-Label Classification for Diagnosis Prediction

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Introduction

❖ Medic Notes based Diagnosis Prediction

- Emergency Medical Service (EMS)
- MIMIC-III ICD-9 Diagnosis Codes
- Long-tail Distribution
- Multi-Label Text Classification (MLTC)

❖ Existing Solutions

Models	Encoder	Attention Mechanism	Knowledge Integration	Knowledge Source	Datasets
(van Aken et al., 2021b) (Yang et al., 2022b) (Bolton et al., 2024)	BERT MegatronBERT GPT2	Self-Attention Self-Attention Self-Attention	Pre-training Pre-training Pre-training	Wikipedia, PubMed Wikipedia, PubMed PubMed	MIMIC-III MIMIC-III MedMCQA
(Mullenbach et al., 2018) (Rios and Kavuluru, 2018) (Li and Yu, 2020) (Zhou et al., 2021)	CNN CNN Multi-filter residual CNN Multi-filter CNN	Label-wise Attention Label-wise Attention Label-wise Attention Shared Interactive Attention	ICD-9 hierarchy graph	ICD-9 description	MIMIC-III MIMIC-III MIMIC-III MIMIC-III
DKEC (Ours)	Multi-filter CNN, Transformers	Label-wise Attention	Heterogeneous graph	Wikipedia, MayoClinic, ODEMSA	MIMIC-III & EMS

❖ Intuition: Domain Knowledge helps

- Compensate for data scarcity in fine-tuning
- Label relations can provide constraints in training

❖ Contribution

- Automated Knowledge Graph Construction by GPT-4
- Knowledge Graph incorporation with language models by heterogeneous label-wise attention
- DKEC outperform SOTAs on two real-world datasets

Knowledge Graph Construction

❖ Information Retrieval

- Description

❖ GPT-4 Chain-of-Thought (CoT) prompt

- Token Classification
- Span Detection
- Relation Extraction

❖ UMLS Concept Normalization

❖ Union of Knowledge Graphs from Multiple Sources

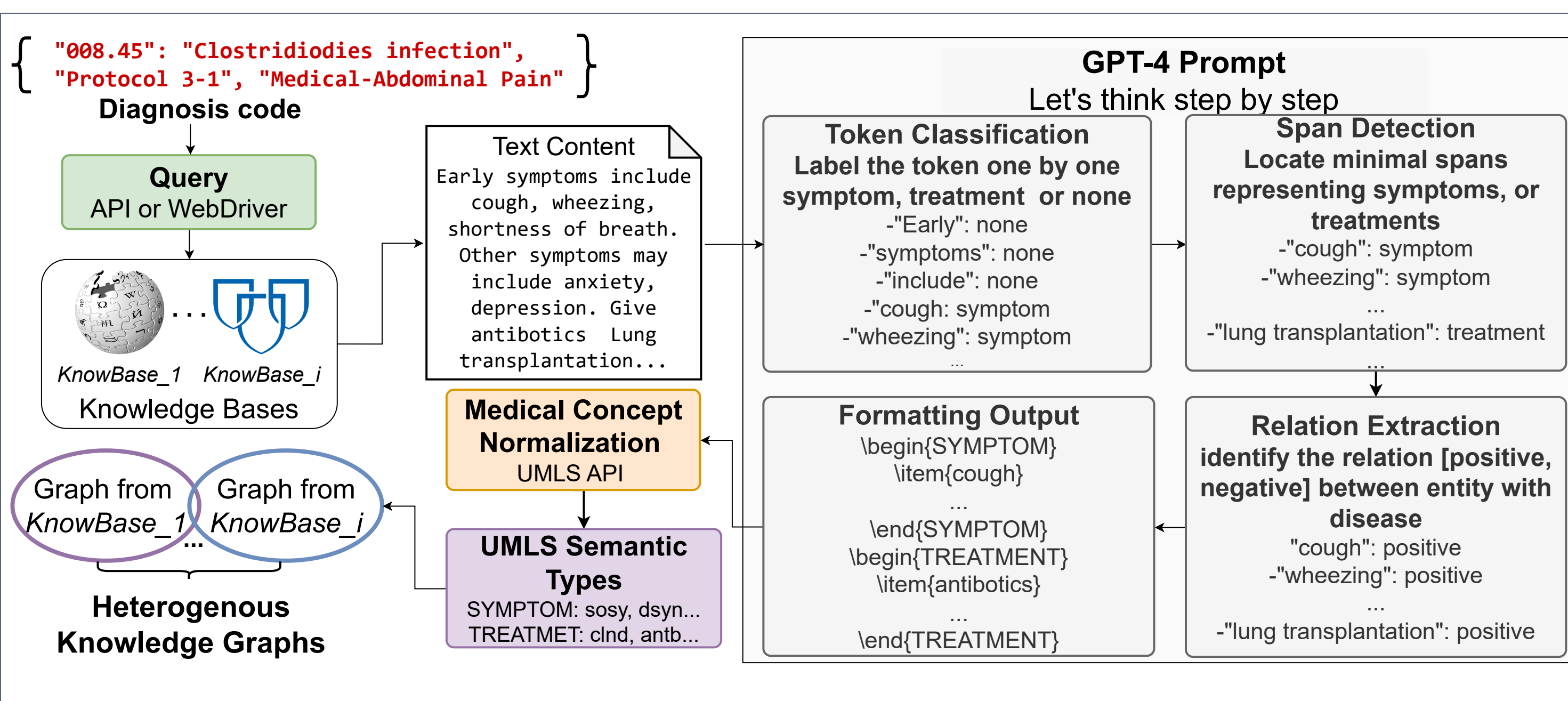


Figure 2: Knowledge Graph Construction

Knowledge Graph Quality Evaluation

❖ Symptoms and Treatments Manual Annotation

❖ 50 ICD-9 Diagnosis Codes

- Wikipedia and Mayo-Clinic

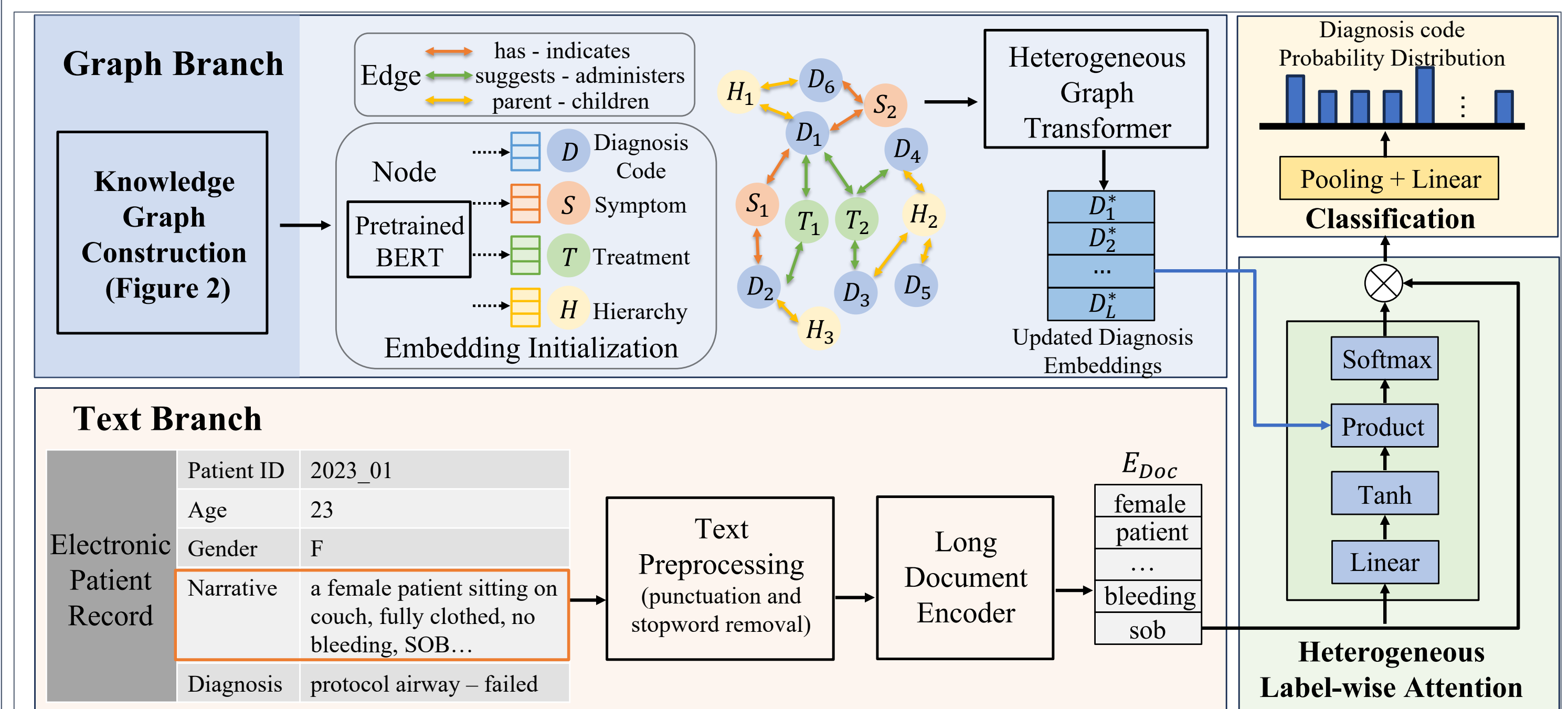
❖ 43 EMS Protocols

- ODEMSA

❖ One-shot CoT GPT-4 outperforms other baselines in medical entity extraction

<i>wo/w NORM</i>	Wikipedia (50 ICD-9 codes)		Mayo Clinic (50 ICD-9 codes)		ODEMSA (43 EMS protocols)	
	Symptom	Treatment	Symptom	Treatment	Symptom	Treatment
MetaMap	47.62 / 51.53	34.66 / 41.95	44.83 / 49.12	41.82 / 46.44	41.34 / 43.61	39.20 / 41.95
cTAKES	48.74 / 52.58	36.01 / 43.35	42.60 / 46.67	39.67 / 45.35	38.02 / 42.47	48.96 / 52.31
ScispaCy	52.79 / 55.57	41.73 / 49.71	46.54 / 50.43	45.94 / 50.89	44.39 / 47.69	35.88 / 38.82
zero-shot GPT-4	51.99 / 58.77	17.93 / 32.13	52.98 / 63.37	26.16 / 36.48	76.07 / 79.72	10.17 / 23.50
one-shot CoT GPT-4	84.63 / 86.57	85.70 / 89.12	82.03 / 86.72	90.43 / 93.90	86.96 / 91.01	86.48 / 88.92

DKEC Pipeline



❖ Graph Branch

- Node: Diagnosis Code $D = \{D_k\}_{k=1}^L$; Symptom $S = \{S_k\}_{k=1}^{|S|}$; Treatment $T = \{T_k\}_{k=1}^{|T|}$; Hierarchy $H = \{H_k\}_{k=1}^{|H|}$
- Edge: Diagnosis Code - Symptom: \vec{E}_{DS} ; Diagnosis Code - Treatment: \vec{E}_{DT} ; Diagnosis Code - Hierarchy: \vec{E}_{DH}
- Heterogeneous Graph Transformer (HGT)
 $D^* = \text{Linear}(\text{HGT}(G))$

❖ Text Branch

$$E_{Doc} = \text{Encoder}(Doc)$$

❖ Heterogeneous Label-wise Attention

- how informative medical document Doc is for all L labels

$$a_{Doc,k} = \text{softmax}(\tanh(W_0 E_{Doc} + b_0) D_k^*)$$

$$A_{Doc} = [a_{Doc,1} \ a_{Doc,2} \ \dots \ a_{Doc,k} \ \dots \ a_{Doc,L}]^T$$

$$E_{Doc}^{attn} = A_{Doc} E_{Doc}$$

❖ Classification

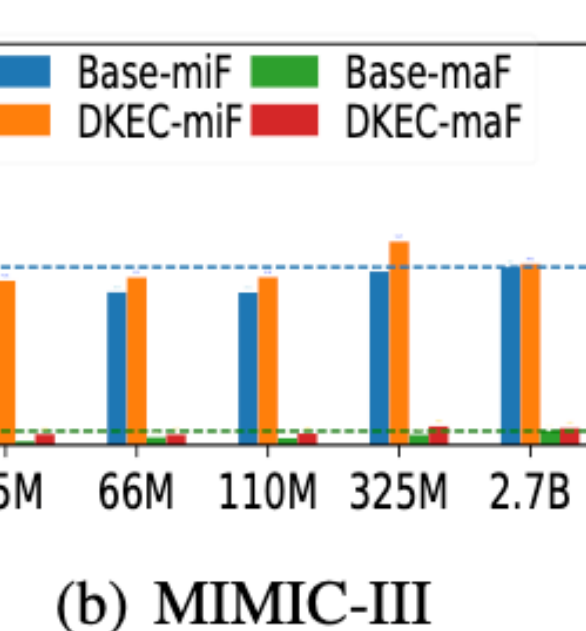
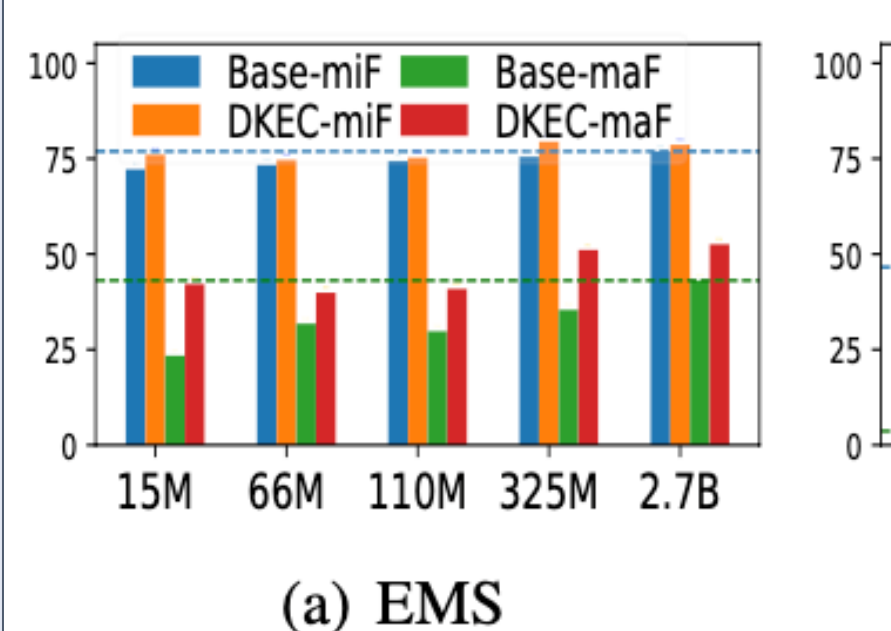
$$\hat{y}_{Doc} = \text{Linear}(\text{Pooling}(E_{Doc}^{attn}))$$

Results

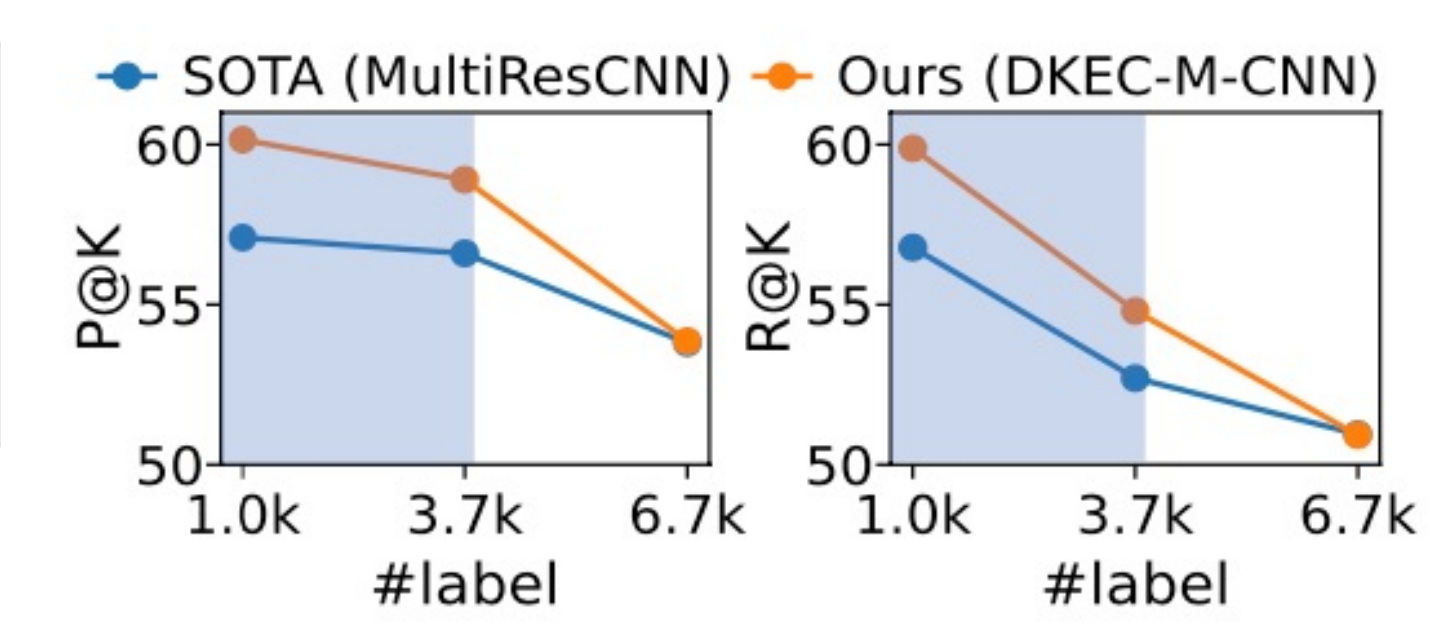
❖ DKEC alleviates the class imbalance problem

		Head Labels		Middle Labels		Tail Labels		Overall			
		P@1	R@1	P@1	R@1	P@1	R@1	miF	maF	P@1	R@1
EMS	CAML	78.6±1.3	77.7±1.3	33.0±0.5	32.6±0.6	22.7±4.5	22.7±4.5	63.7±1.2	22.4±1.3	65.0±1.6	63.5±1.5
	ZAGCNN	83.0±1.0	82.0±1.0	47.0±1.0	46.2±0.7	37.9±7.7	37.9±7.7	64.8±1.1	28.3±2.0	69.6±0.7	68.1±0.6
	MultiResCNN	84.3±0.2	83.2±0.2	35.6±1.8	35.0±2.0	25.0±2.3	25.0±2.3	65.8±0.2	26.1±0.5	67.9±0.3	66.3±0.3
	ISD	81.7±0.9	80.8±0.9	44.2±0.4	43.2±0.5	29.5±2.3	29.5±2.3	67.1±1.2	26.1±0.1	68.0±1.3	66.5±1.2
	GatorTron	89.4±0.5	88.4±0.5	66.0±0.4	64.7±0.7	57.1±2.2	57.1±2.2	75.5±0.6	35.4±1.9	77.3±0.6	75.4±0.6
	BioMedLM	89.3±0.3	88.2±0.3	71.3±0.7	70.1±0.6	47.6±4.3	47.6±4.3	76.9±0.7	43.1±1.7	78.4±0.6	76.6±0.6
MIMIC-III	DKEC-M-CNN	85.2±0.7	83.0±0.7	53.2±1.3	52.7±1.1	45.1±2.1	45.1±2.1	68.6±0.4	32.4±0.6	72.4±0.4	71.7±0.6
	DKEC-GatorTron	91.8±0.1	90.7±0.1	72.4±0.4	71.3±0.4	67.6±2.3	67.6±2.3	79.5±0.5	51.1±1.5	82.2±0.5	80.3±0.6
	CAML	54.8±0.5	57.5±0.6	5.5±0.4	28.4±2.3	0.7±0.1	4.8±0.5	51.5±0.7	4.3±0.5	54.4±0.5	50.3±0.5
	ZAGCNN	55.3±0.2	58.0±0.2	6.6±0.1	34.4±0.7	1.8±0.1	11.7±0.8	52.1±0.4	4.0±0.3	55.2±0.2	51.2±0.3
MIMIC-III	MultiResCNN	56.5±0.3	59.4±0.2	8.2±0.5	42.3±2.8	1.2±0.1	7.5±0.9	55.6±0.3	6.0±0.6	56.6±0.2	52.7±0.2
	ISD	51.8±0.5	53.8±0.5	6.1±0.2	31.7±1.2	1.9±0.2	12.6±0.9	46.8±1.3	2.8±0.2	51.6±0.5	47.5±0.5
	GatorTron	50.4±0.2	53.4±0.2	6.5±0.2	33.8±1.1	2.0±0.3	12.7±1.4	45.4±0.4	2.7±0.3	50.3±0.2	47.1±0.2
	BioMedLM	50.5±0.1	53.4±0.1	6.1±0.1	31.3±1.2	2.0±0.1	13.2±1.1	46.6±0.3	3.7±0.5	50.2±0.1	47.2±0.2
	DKEC-M-CNN	58.6±0.2	61.5±0.2	9.6±0.1	49.2±0.8	2.9±0.1	19.2±0.9	55.0±0.3	4.9±0.2	58.9±0.2	54.8±0.2
	DKEC-GatorTron	56.8±0.4	59.8±0.2	8.5±0.1	44.7±0.7	3.1±0.2	19.1±1.1	53.0±0.4	5.7±0.3	56.9±0.4	53.2±0.3

❖ DKEC enables smaller language models to achieve comparable performance to LLMs



❖ DKEC maintains performance when external knowledge is available for all the labels



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