Doctor Recommendation in Online Health Forums via Expertise Learning



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Introduction

Motivation

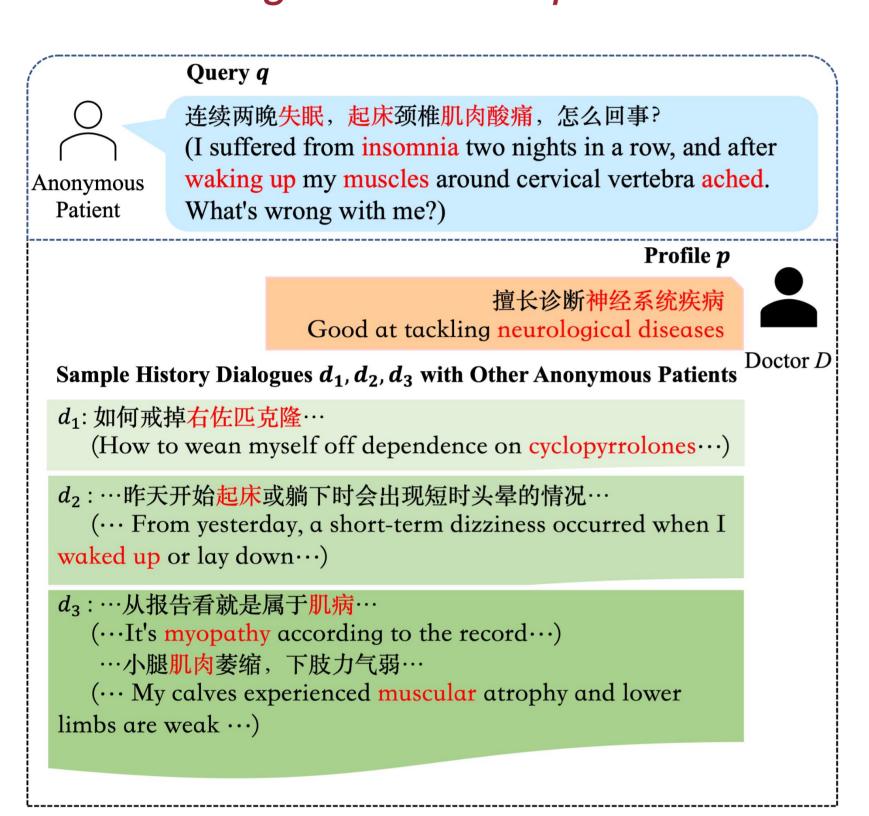
- Massive amounts of patients go to online health forums for help.
- Labor-intensive to assign doctors manually (common practice).
- Important to automate the doctor-patient matching with NLP.

Challenges

- Patients' needs should be learned from a short query.
- Different languages styles of doctor profiles and patient queries.

Contributions

- A novel task of doctor recommendation to learn the matching of a doctor's expertise and a patient's need.
- A new dataset for doctor expertise learning through their profiles and past dialogues.
- Comprehensive experiments to investigate the automatic learning of doctor expertise on the realistic social media data.



Input:

• A doctor D

- Doctor Profile
- History dialogues
- with other patients
- A patient P
 - Patient Query

Output:

 How likely D has the expertise to help P.

Related Work

Recommender Systems

 Employ rich user history to learn their interests (unavailable here because of the anonymized patients).

NLP for Medical Study

- Focus on the understanding of medical text.
- Limited attempts to examine expertise learning for doctors.

Dataset

Data Statistics

Our dataset collected from Chunyu Yisheng is *large-scale*,
 diverse across different medical departments and contains *rich information*.

# of dialogues	119,128
# of doctors	359
# of departments	14
# of tokens in vocabulary	8,715
Avg. # of dialogues per doctor	332
Avg. # of doctors per department	26
Avg. # of tokens in a query	90
Avg. # of tokens in a dialogue	534
Avg. # of tokens in a profile	88

Data Analysis

- 86% of doctors are involved in over 100 dialogues and 84% dialogues contains over 200 tokens.
- Doctors use *more professional language* in their profile (30.13% of tokens measured by the THUOCL medical lexicon), while adapting to *layman's language* in conversations (7.83% and 5.52% for patient and doctor turns).

Our Model

Self-Learning Task

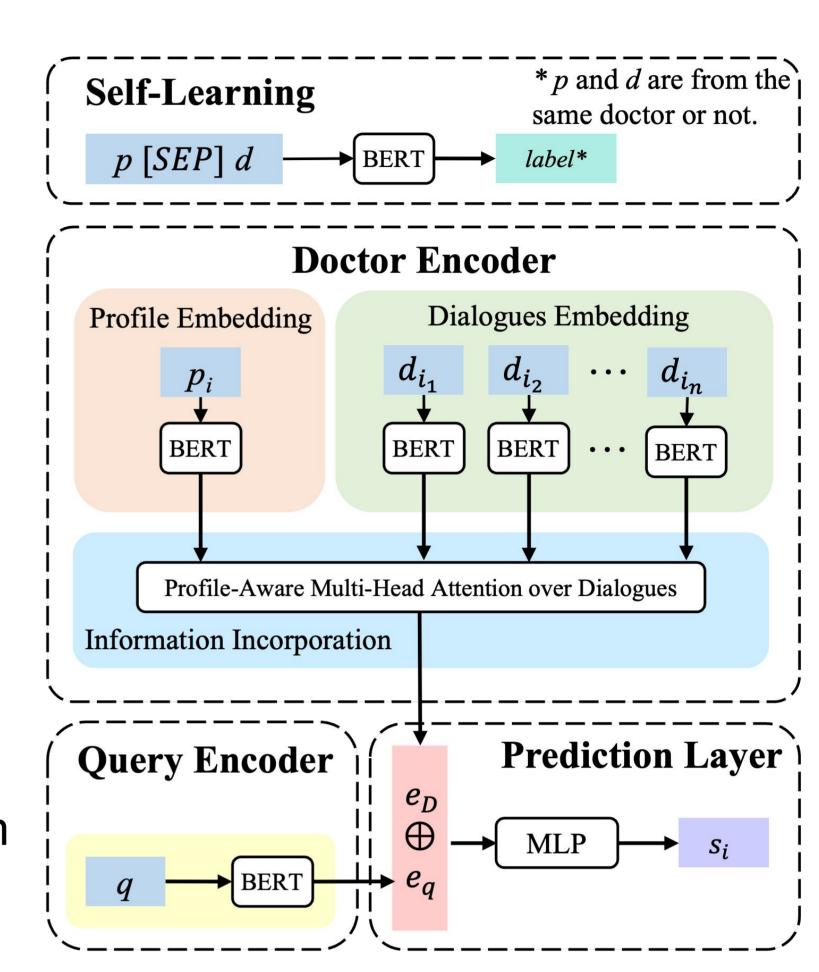
Fill in the *language styles gap* between profiles and dialogues.

Text Encoder

- Profiles and queries are encoded *directively* with BERT.
- Dialogues are treated as a concatenated chronological turns.

Multi-head Attention

 Incorporate information from profiles and dialogues into doctor representation.



Prediction

 Output expert degree based on the pair of query embedding and doctor embedding.

Experimental Results

Madala	D@1	MADE	EDD@5
Models Simple Pacelines	P@1	WAPE	ERR@5
Simple Baselines			
Random _	0.010	0.052	0.001
Frequency	0.005	0.032	0.001
KNN	0.082	0.151	0.008
Cos-Sim (P+Q)	0.049	0.122	0.005
Cos-Sim (D+Q)	0.056	0.136	0.006
GBDT	0.018	0.052	0.002
Neural Comparisons			
MLP (P+Q)	0.164	0.331	0.018
MLP (D+Q)	0.174	0.341	0.019
MLP (P+D+Q)	0.153	0.312	0.017
DSSM (BERT with D)	0.087	0.182	0.009
DSSM (BERT with P)	0.151	0.231	0.012
Dot-Att	0.219	0.38	0.021
Cat-Att	0.167	0.332	0.018
Our Ablations			
Mul-Att (w/o SL)	0.309	0.319	0.019
Mul-Att (w/o D)	0.198	0.217	0.013
Mul-Att (w/o P)	0.521	0.526	0.033
Mul-Att (full)	0.616	0.620	0.039

Attention Heads Analysis

Head i	Top 5 Keywords
1	muscle, nerve, convulsion, weakness, atrophy
2	dizziness, nerve, headache, internal medicine, sickness
3	nerve, muscle, ache, strain, massage
4	sleep, anxiety, insomnia, nerve, Dexzopiclone
5	muscle, neck, headache, sickness, cervical vertebrae
6	nerve, muscle, neck, ache, lumbar vertebrae

- Attention heads for Introduction example have *different focuses* (top 5 medical terms attended by each head vary).
- All heads are related to the queried symptom of "insomnia" and "muscle ache" in neurology.