Task-oriented Dialogue System for Automatic Diagnosis

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Introduction

Our research aims to develop an task-oriented dialogue system that makes the diagnosis for patients automatically, which can converse with patients to collect additional symptoms.

- Most works involving automatic diagnosis is based on electronic health records (EHRs), which is very expensive to collect.
- Task-oriented dialogue system (DS) has been well researched and reached a promising performance in some specific tasks.
- The cost of collecting data from patients will be reduced greatly by applying DS to medical domain.

Contributions:
- We annotate the first medical dataset for dialogue system.
- We proposed a reinforcement learning based framework for medical DS.

Dataset

- Collected from the pediatric department in a Chinese online healthcare community.
- Three annotators are invited to label all the symptom phrases in both self-reports and conversational data.

- Self-report
  - Symptoms: 腹泻
  - Does the baby have diarrhea now?
  - Doctor: 腹泻
- Conversation
  - Patient: No, but I had a diarhea.
  - Doctor: 腹泻
  - Patient: My baby has been feeling a little bit hot.

Symptom Extraction:
- Each Chinese character is assigned a label of “B”, “I” or “O”.
- Each extracted symptom expression is tagged with True or False indicating whether the symptom exists in this symptom.
- The Cohen’s kappa coefficient between annotators are 71% and 67% for self-reports and conversations respectively.

Symptom Normalization:
- Each symptom expression is linked to the most relevant concept on SNOMED CT for normalization.
- User goals are derived from user records.

![Example of a user goal](image)

- **disease_tag** is the disease that the user suffers.
- **explicit_symptoms** are symptoms extracted from the user self-report.
- **implicit_symptoms** are symptoms extracted from the conversational data.
- **request_slots** is the disease slot that the user would request.

<table>
<thead>
<tr>
<th>Disease</th>
<th>SVM-ex &amp; im</th>
<th>SVM-ex</th>
</tr>
</thead>
<tbody>
<tr>
<td>Infantile diarrhea</td>
<td>0.91</td>
<td>0.89</td>
</tr>
<tr>
<td>Children functional dyspepsia</td>
<td>0.34</td>
<td>0.28</td>
</tr>
<tr>
<td>Upper respiratory infection</td>
<td>0.52</td>
<td>0.44</td>
</tr>
<tr>
<td>Children’s bronchitis</td>
<td>0.93</td>
<td>0.71</td>
</tr>
<tr>
<td>Overall</td>
<td>0.71</td>
<td>0.59</td>
</tr>
</tbody>
</table>

Table 2. Accuracy of classification models

<table>
<thead>
<tr>
<th>Model</th>
<th>Success</th>
<th>Reward</th>
<th>Turn</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Agent</td>
<td>0.06</td>
<td>-24.36</td>
<td>17.51</td>
</tr>
<tr>
<td>Rule Agent</td>
<td>0.23</td>
<td>-13.78</td>
<td>17.00</td>
</tr>
<tr>
<td>DQN Agent</td>
<td>0.65</td>
<td>20.51</td>
<td>5.11</td>
</tr>
</tbody>
</table>

Table 3. Performance of dialogue system

<table>
<thead>
<tr>
<th>Disease</th>
<th>Ave # of implicit symptoms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Infantile diarrhea</td>
<td>2.13</td>
</tr>
<tr>
<td>Children functional dyspepsia</td>
<td>1.70</td>
</tr>
<tr>
<td>Upper respiratory infection</td>
<td>2.56</td>
</tr>
<tr>
<td>Children’s bronchitis</td>
<td>2.87</td>
</tr>
</tbody>
</table>

Table 1. Overview of the dataset

Figure 1. An example of user goal

Figure 2. Learning curve of policy learning

User Simulator
- Sampling a user goal from the experiment dataset to initiate a dialogue session.
- Taking one of the three actions including True, False and not sure.
- The dialogue session will be terminated as successful by the user if the agent informs correct disease. Otherwise it will be terminated as failed.

Dialogue system
- Both natural language understanding and natural language generator are implemented with template-based models.
- Dialogue state consists of the symptoms requested by the agent and informed by the user till the current time t, the previous action of the user, the previous action of the agent and the turn information.
- An action is composed of a dialogue act and a slot.
- The dialogue policy is trained via DQN.
- ε-greedy and experience replay are applied.

Experiments and Results

Experimental setup:
- The maximum dialogue turn is 22.
- The reward for successful and failure dialogue session are +44 and -22 respectively.
- A step penalty of -1 for each turn is applied.
- 80% of the user goals for training and 20% for testing.

Metrics:
- success rate, average reward, average number of turns per dialogue session.

Baseline:
- SVM: takes the automatic diagnosis as a multi-class classification problem.
- SVM-ex & im: takes both explicit and implicit symptoms as input.
- SVM-ex: takes only explicit symptoms to predict the disease.
- Random agent: takes an action randomly at each turn.
- Rule-based agent: takes an action based on handcrafted rules.