

Dialog State Tracking and Action Selection Using Deep Learning Mechanism for Interview Coaching

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Introduction

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- While in school, students are busy in studying for a better future.
 - Students rarely have the opportunity to practice interview for work or study.
- If students are afraid or nervous during the interview,
 - they can not answer questions asked by the interviewers properly.



Motivation and Goal

In this study, we proposed a coaching system to improve user's interview skills.



Motivation and Goal

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- How to select a proper question plays an important role in a coaching system.
 - Dialog state tracker and dialog action selection model need to be constructed first.
 - According to the information provided, a coaching system can select a proper question to ask users.

Data collection and annotation

- Interview dialog corpus collection:
 - The domain of the corpus is chosen as the College Admission Interview.
 - **12** participants were invited.
 - During corpus collection, two participants completed the interview without prior design questions and answers.
 - A total of 75 dialogs with 540 question and answer pairs were collected.
 - Average number of sentences for each answer is 3.95.

Data collection and annotation

According to the collected corpus,

6 categories and **10** semantic slots were defined.

Category	Semantic Slot
Studying experiences	Community and cadres
	Score and other achievement
Interests, and strengths and weaknesses	Interest
	Strength and weakness
Learning motivation and future prospects	Motivation
	Reading plans and future plans
Domain knowledge	Professional field and curriculum
	Programming language and specialized terms
Personality trait	Personality
Others	Others

System Framework



Word embedding model

- Each word is mapped to its corresponding word vector
 w_i by using word2vec.
 - Word2vec creates vectors that are distributed numerical representations of word features, such as the context of individual words.
 - The purpose and usefulness of word2vec is to group the vectors of similar words together in the vector space.
 - Word2vec encodes each word in a vector and trains words against other words that neighbor them in the input corpus.

Word embedding model

- This study uses the Skip-gram model.
 - We use Chinese Gigaword corpus to train word2vector.
 - □ Totally, 42619 words were obtained.
 - The word vector is connected to the vector representation of the sentence.



Dialogue State Tracking

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- Sentence and answer hidden vector representation:
 - Considering semantic representation of each sentence in an answer.



Dialogue State Tracking

Dialog state representation:

- Using 10 ANN models, each for one slot.
- □ The input of ANNs is the answer hidden vector.
- Compose all slot values to form a dialog state



Dialog Action Selection

Training action selection model and question generation model.



Dialog Action Selection

Deep Q network Pre-training



Experimental setup

- Action selection model
 - Reward curve was approximate to 1
 - Deep Q-network nodes:100
 - □ Mini-batch:64
 - Experience size:10000
 - Number of Training Simulated Dialogs : 1000



Experimental results (1)

Evaluation the action selection model with different reward function

1-0 reward function :

$$r_t^i = \begin{cases} 1, & \text{if } Na_t^i = 0 \text{ or } 1\\ 0, & \text{otherwise} \end{cases}$$

Number of completed actions:

$$r_t^i = \begin{cases} AR, & \text{if } Na_t^i < 2\\ 0, & \text{otherwise} \end{cases}$$

SimpleDS reward function:

$$r_t^i = CR * 0.5 + DR * 0.5$$

Reward function	Slots-turns ratio (slots/turn)
1-0 reward	0.92
Completed actions	0.89
SimpleDS	0.86

- N_{a_t} is the number of the *i*-th action which has been positively confirmed at time t
- *AR* is the number of actions positively confirmed divided by the actions to confirm
- *CR* is the number of slots positively confirmed divided by the slots to confirm, *DR* as $p(a_t|s_t)$

Experimental results (2)

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- We analyze the average number of completed slots, the average dialog turns and their ratio with different architectures.
 - Testing with 1000 simulated dialogs.

	Avg. Number of Completed slots	Avg. turns	Standard Deviation (turns)	Slots-turns ratio (slots/turn)
w-Restriction + w/Pre-training	7.77	8.44	0.75	0.92
w-Restriction + w/o-Pre-training	7.74	8.51	0.74	0.91
w/o-Restriction + w/Pre-training	7.04	8.40	4.04	0.84
w/o-Restriction + w/o-Pre-training	7.82	10.56	2.63	0.74
w : with, w/o : without				

Experimental results (3)

- Question selection model evaluation:
 - We use questionnaire to evaluate Naturalness and Utility
 - Naturalness : The semantic content of question from system is ideal
 - □ Utility : The system flow is applicable
 - 5 subjects were invited
 - 5-level Likert scale

	Mean	Standard Deviation	t-value
Naturalness	3.80	0.447	4.00**
Utility	3.60	0.548	2.45**

Conclusions

- We propose an approach for dialog state tracking and dialog action selection in an interview conversation.
 - The word2vec model is employed for word distributed representation.
 - The LSTM+ANN-based model is used to predict dialog states.
 - The deep RL-based model is used to learn the relation between dialog states and actions..
- In the future, a richer interview corpus and a robust DST model are helpful to improve system performance.





Questions?