Hierarchical Context Enhanced Multi-Domain Dialogue System for Multi-domain Task Completion

Jingyuan Yang, Guang Liu*, Yuzhao Mao, Zhiwei Zhao, Weiguo Gao, Xuan Li, Haiqin Yang, Jianping Shen

{yangjingyuan743,liuguang230}@pingan.com.cn
{maoyuzhao258,zhaozhiwei387,gaoweiguo801,lixuan208,yanghaiqin260,shenjianping324}@pingan.com.cn

Abstract

Task 1 of the DSTC8-track1 challenge aims to develop an end-to-end multi-domain dialogue system to accomplish complex users goals under tourist information desk settings. This paper describes our submitted solution, Hierarchical Context Enhanced Dialogue System (HCEDS), for this task. The main motivation of our system is to comprehensively explore the potential of hierarchical context for sufficiently understanding complex dialogues. More specifically, we apply BERT to capture token-level information and employ the attention mechanism to capture sentence-level information. The results listed in the leaderboard show that our system achieves first place in automatic evaluation and the second place in human evaluation.

Introduction

Task-oriented dialogue systems aim to help users to accomplish specific tasks, e.g., booking a ticket, checking the weather. An intelligent dialogue system can significantly reduce labour expenses and improve work efficiency. Due to its promising prospect in many areas, developing intelligent dialogue systems draws much attention in both academia and industry.

Generally, a dialogue system consists of three components (Mehri, Srinivasan, and Eskenazi 2019): the natural language understanding (NLU) module, the dialogue management (DM) module, and the natural language generation (NLG) module. The NLU module is the entry to the whole system and needs to correctly understand an inputted utterance to guarantee the performance of the rest components. The DM module receives the output from the NLU module, maintains the dialog states (DS), and predicts the system actions through designed policy. The NLG module takes system actions as input to generate responses, which fulfil users requests.

Early studies usually build dialogue systems to deal with simple users goals within a single domain (Williams et al. 2013, Mrkšić et al. 2016, Mairesse et al. 2009, Yan et al. 2017, Wen et al. 2016, Li et al. 2017, Peng et al. 2017). However, real-world dialogue systems usually need to deal with complex users goals spanning over multiple domains. Recent studies take much effort to explore the methods in constructing multi-domain dialogue systems (Ultes et al. 2017, Miller et al. 2017). Unlike single domain dialogue systems, a multi-domain dialogue system may encounter domain ambiguity because of slot overlapping and lacking context information (Rastogi, Hakkani-Tür, and Heck 2017). For example, there is no clear clue to infer the domain of the utterance “I want free parking”. It may happen in the domain of HOTEL, ATTRACTION or any others proper domains. With sufficient context information, the domain can be easily inferred to understand users need.

To further explore the potential of dialog context, we propose a Hierarchical Context Enhanced Dialogue System (HCEDS). More specifically, we utilize token-level contextual information encoded from BERT, and sentence-level contextual information from utterance guided attention on dialogue history for better understanding user utterance. As a result, HCEDS achieves the best performance in success rate, precision, recall and f1 scores through machine evaluation, and the second place in human evaluation.

The rest of this paper is organized as follows. First, we give a short review of related work. Second, the task definition is described. Third, the architecture of HCEDS is reported. Next, the experimental settings are presented. Then, the experimental results and analysis are given. Last, the conclusion is delivered.

Related Works

Modular task-oriented dialogue systems achieve promising results in various scenarios. It usually consists of three components: the NLU module, the DM module, and the NLG module. In this section, we make a brief review of them.

Usually, the NLU module in multi-domain dialog systems consists of classifiers or sequence-taggers, which try to categorize the corresponding domains, intents, and slots. Pre-
viously proposed multi-domain NLU modules apply independent classifiers to categorize them, but ignore the complementary information among domains (Mairesse et al. 2009). To address this issue, ONENET (Kim, Lee, and Stratos 2017) assumes that an utterance belongs to one specific domain and jointly learns three classifiers exploring the complementary information of multiple domains. However, an utterance usually belongs to multiple domains and may contain multiple intents. MILU (Lee et al. 2019) applies multi-label classification setting and proposes an integrated classifier to classify domains and intents simultaneously. However, without clear domain information, the domain-intent-slot triplets may be in multi-turn dialogue (Rastogi, Hakkani-Tür, and Heck 2017). It still needs much effort to explore contextual information to enhance the domain-intent-slot categorization.

The objective of the DM module is to a dialog state tracker (DST) to track dialogue states and to choose appropriate decisions based on dialogue policy. For multi-domain DST, rnn-based models using Gated Recurrent Units (GRU) (Rastogi, Hakkani-Tür, and Heck 2017), Bidirectional Long Short-Term Memory (BiLSTM) (Ramadan, Budzianowski, and Gašić 2018) have been applied. Rule-based DST is another branch of active methods in the community (Williams et al. 2013). In terms of dialogue policy learning, they can be categorized into rule-based, supervise-based (DeVault, Leuski, and Sagae 2011) and reinforcement learning (RL) based methods (Cuayáhuitl, Keizer, and Lemon 2015), respectively. Recently, due to lack of enough data for learning well-set dialogue policy (Schatzmann et al. 2006), RL based methods are intensively investigated.

The objective of the NLG module is to convert system actions processed from DM to natural language. Template-based NLG (Lee et al. 2019) is the simplest, yet efficient approach to extract system actions from DM. It maps input semantic symbols into tree-like or template structures and converts the intermediate structures into sentences, which respond to users requests. (Walker, Rambow, and Rogati 2002). Neural network-based approaches, e.g., LSTM-based structure with the Recurrent Neural Network Language Model (RNNLM) loss (Wen et al. 2015a), have been popularly applied for NLG (Wen et al. 2015b). The user simulator is built by obeying the static from MultiWOZ. Additional annotations for user dialog acts are further annotated for multi-domain NLU research.

Hierarchical Context Enhanced Dialogue System

Figure 2 illustrates our designed Hierarchical Context Enhanced Dialogue System (HCEDS), which consists of following three modules.

\[ \text{HCEDS} = \langle \text{HCENLU},\ \text{DM},\ \text{MINLG} \rangle, \]

where \( \text{HCENLU} \) is our proposed NLU module (namely Hierarchical Context Enhanced NLU), \( \text{DM} \) is our refined Dialogue Management module, and \( \text{MINLG} \) is our proposed Multi-Intent NLG module.

Hierarchical Context Enhanced NLU

The HCENLU parses a user’s utterance into a triplet corresponding to the value in domain, intent and slot, respectively. For example, typical triplet lies in \{Hotel – Request : [Price : cheap, Parking : yes]\}. To resolve the problems of domain ambiguity and slot overlapping in multi-domain dialogues, we parse utterance by utilizing contextual information across different semantic levels. Different from the Hierarchical attention networks (HAN) (Yang et al. 2016) for document classification, we apply BERT \(^1\) with self-attention mechanism to capture context information within a sentence, and utilize the attention mechanism (Luong, Pham, and Manning 2015) to absorb related context information from multi-turns dialogue history according to the user’s utterance. As shown in Figure 3, HCENLU contains four different layers: 1) input layers 2) token encoder layer 3) sentence encoder layer 4) output layer

\( \text{Input layer} \) has two sources of input, Users’ Utterances (UU) and the Dialogue Context, namely

\(^1\)The pre-trained model and source code are from https://github.com/huggingface/transformers/tree/v0.6.1

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**Task description**

Task1 of DSTC8-track1 aims to encourage participants to build an end-to-end multi-domain dialogue system under the setting of the Tourist Information Desk. They provide an open-source dialog system platform, ConvLab (Lee et al. 2019), which provides off-the-shelf APIs for quickly setting up experiments. To fully evaluate the submitted dialogue systems, DSTC8 offers two evaluating strategies which are simulation-based evaluation and crowdworker-based evaluation.

As shown in Figure 1, the task is based on the Multi-Domain Wizard-of-OZ (MultiWOZ) (Budzianowski et al. 2018), which is a large-scale multi-domain dialogue dataset containing seven domains related to traveling. The ConvLab provides a convenient interface and reference models for MultiWOZ dataset. The user simulator is built by obeying the static from MultiWOZ. Additional annotations for user dialog acts are further annotated for multi-domain NLU research.
past $w$ turn dialogues (DC). UU is a token sequence $X_{uu} = x_1, x_2, \ldots, x_m$, where $m$ is the number of tokens of UU. The DC stacks previous $w$-turn dialogue, and is represented as a sequence of tokens which is $X_{dc} = x_1, x_2, \ldots, x_n$, where $n$ is the total number of tokens of DC.

Token-level encoder encodes the aforementioned two sources of sequences into contextualized token-level representation, which are transformed to token embeddings, and fed into Bi-directional LSTM (BiLSTM), which uses two LSTM (Hochreiter and Schmidhuber 1997) in opposite input order, to acquire contextualized token level representation.

A three-step progress is carried out to get the token level representation for each input source. Firstly, the tokenized inputs are fed into a pre-trained BERT (Devlin et al. 2018) to obtain the embeddings $e_{bert}$. Secondly, each token is fed into a Char Convolutional Neural Network (CharCNN), which is a modified convolutional neural network (LeCun et al. 1998), to obtain a char embeddings $e_{cnn}$. Then, we concatenate two embeddings to obtain the token embedding $e_{token}$. Given an input token $x_i$, the token embedding is calculated as follows,

$$e_{token} = e_{bert} \oplus e_{cnn}.$$  \hspace{1cm} (2)

To this end, the token embeddings, UU ($e_{token}^{uu}$) and DC ($e_{token}^{dc}$), are obtained from the aforementioned two sources of sequence input. The token embeddings are fed into two independent BiLSTM separately obtaining the token-level representations which is,

$$h_{sentence}^{uu} = \text{BiLSTM}_{uu}(e_{token}^{uu}),$$  \hspace{1cm} (3)

$$h_{sentence}^{dc} = \text{BiLSTM}_{dc}(e_{token}^{dc}).$$  \hspace{1cm} (4)

Sentence level encoder encodes the token-level representation into sentence-level representation for domain-intent classification and tag labeling. Firstly, we input the token level representations of UU into two independent BiLSTM as follows,

$$h_{intent}^{uu} = \text{BiLSTM}(h_{sentence}^{uu}),$$  \hspace{1cm} (5)

$$h_{tag}^{uu} = \text{BiLSTM}(h_{sentence}^{uu}).$$  \hspace{1cm} (6)

Here, $h_{domain-intent}^{uu}$ is the hidden states for domain-intent classification, $h_{tag}^{uu}$ is the hidden states for tag labeling. Secondly, we calculate the attended context vector using bilinear attention method (Luong, Pham, and Manning 2015), which uses the last hidden state of $h_{domain-intent}^{uu}$ to guide the calculation of attention weights from $h_{sentence}^{dc}$,

$$c^{dc} = \text{Attention}(h_{intent}^{uu}, h_{sentence}^{dc}),$$  \hspace{1cm} (7)

where $c^{dc}$ is the attended context vector, the last state of $h_{intent}^{uu}$ is the query and the $h_{sentence}^{dc}$ is the key and value. Finally, we concatenate three contextual vectors, $c^{dc}$ and the last hidden states of $h_{sentence}^{dc}$ and $h_{domain-intent}^{uu}$, as the sentence-level representation for domain-intent classification.

$$h_{concat}^{uu} = c^{dc} \oplus h_{sentence}^{dc} \oplus h_{intent}^{uu}.$$  \hspace{1cm} (8)
Here, $h_{\text{concat}}^{\text{domain-intent}}$ is the sentence-level representation for the domain-intent classification.

We also can get the sentence-level representation for slot labeling.

$$h_{\text{concat}}^{\text{tag}} = c^{\text{dc}} \oplus h_{\text{dc}}^{\text{sentence}} \oplus h_{\text{au}}^{\text{tag}}, \quad (9)$$

where $h_{\text{concat}}^{\text{tag}}$ denotes the sentence-level representation for slot labeling.

$Output$ project projects the sentence level representations into the form of domain-intent classification or slot labeling. $h_{\text{concat}}^{\text{domain-intent}}$ is fed to a multi-label classifier for domain-intent classification. For slot labeling, we apply softmax at each time-step of $h_{\text{concat}}^{\text{tag}}$ layer for tag labeling. We use BIOX tag to adapt Byte-Pair Encoding (BPE) (Sennrich, Haddow, and Birch 2015) strategy.

**Dialogue Management**

This module consists of two submodules, Dialogue State Tracking (DST) and System Policy (SP).

DST uses the default method provided by ConvLab to track dialog state (Williams et al. 2013). Its inputs are user actions parsed from NLU, and the dialog state $S_{t-1}$ at time $t−1$. Its output is the dialog state $S_{t}$ at time $t$, which was updated by recording user actions from time $t$ to $t−1$.

SP refines the provided rule-based system policy by carefully tuning rules through bad case analysis. Its input is the dialog state $S_{t}$ at time $t$, and its output is the system action $A_{t}$ at time $t$, which can be represented as domain-intent-slot triplets.

| Table 1: Example of Policy |
|-----------------------------|
| **Input**                  |
| Dialog State $S_{t}$       |
|                             |
| **Output**                 |
| System Action $A_{t}$      |
|                             |

| **System Action** | **Generated Response** |
|-------------------|------------------------|
| `{Type: 'college'}`, `{Phone, 01223336265}` | The attraction phone number is 01223336265. The attraction postcode is cb21jf. |
| `{Post, cb21jf}`  | The attraction postcode is cb21jf. |

**Multi-intent NLG**

Multi-intent NLG (MINLG) extends the default language generating template from single-intent to multi-intent. It means that a system action may have more than one slot-value pairs. We would try to search related multi-intent templates rather than using single-intent template many times. The multi-intent templates are mined from the MultiWoz Dataset. Table 3 lists an example of multi-intent templates.

**Algorithm 1** Refined Rule Policy

**Input**: Dialog State $S_{t}$

**Output**: System Action $A_{t}$

**Initialize**: System Action List $A = []$

**Domain List** $D = [\text{hotel, restaurant, police, taxi, attraction, hospital, train}]$

1: **for** domain, intent, slot in $S_{t}$ **do**
2: \hspace{1cm} $db_result = query\_db(\text{domain, intent, slot})$
3: \hspace{1cm} if intent is request then
4: \hspace{2cm} if domain in $D$ then
5: \hspace{3cm} $A.add(request\_policy(db\_result, domain, slot))$
6: \hspace{1cm} end if
7: \hspace{1cm} else if intent is inform then
8: \hspace{2cm} if domain in $D$ then
9: \hspace{3cm} $A.add(inform\_policy(db\_result, domain, slot))$
10: \hspace{1cm} end if
11: \hspace{1cm} else
12: \hspace{2cm} $A.add(\text{general\_policy(domain, intent, slot)})$
13: \hspace{1cm} end if
14: **end for**
15: **return** merge\_rule($A$)

Obviously, multi-intent templates based NLG is able to generate more natural responses than single-intent templates based NLG.

**Table 2**: Comparision of single-intent templates based and multi-intent templates based NLG.

**Experiments**

In this section, we first outline the experimental environment and setup. Then, we discuss the quantitative results. Last, we illustrate an example of our dialogue system.

**Experimental environment**

**Platform**. The DSTC8-track1 challenge provides ConvLab, a platform consisting of a rich set of runtime engines, for building a multi-domain end-to-end dialogue system. With a set of reusable components provided by ConvLab, approaches ranging from conventional pipeline systems to end-to-end neural models can be effortlessly developed and conveniently compared in a common platform. Our proposed HCEDS is deployed and evaluated in the ConvLab platform.

**Dataset**. We mainly apply the MultiWOZ dataset to develop HCENLU. The MultiWOZ dataset consists of 10,438...
dialogues, a fully-annotated collection of human-human conversations related to tourists ranging over 7 domains, i.e., attraction, hospital, police, hotel, restaurant, taxi and train. The statistic of the dataset is listed in Table 3. We follow the standard setting and split the training, validating and test as 8,438, 1,000, and 1,000, respectively.

Training Settings. Letters are turned into lower case and words are encoded by BPE. The BIOX scheme is applied with BPE. We apply both Bert and CharCNN to represent utterances. The character embedding size is 16. The number of filter and the windows size for CharCNN are 128 and 3, respectively. BiLSTMs, shared the same model structure, are applied to obtain token-level representations, where the input size and the size of the hidden layer are 896 and 200, respectively. In addition, BiLSTMs, shared the same model structure, are applied to obtain sentence-level representations, where the input and hidden size are 400 and 200, respectively. The dropout rate is 0.5 for all BiLSTMs. ADAM (Kingma and Ba 2014) is adopted as the optimizer with the initial learning rate being 0.001 and the gradient norm being 5.0.

Evaluation. Two evaluation metrics, simulation-based evaluation and crowdworker-based evaluation, are applied to evaluate the performance of each submitted dialogue system. Besides, we design another two evaluation strategies to measure the effect of our HCENLU and the importance of other modules. The details of these four evaluation metrics are described as follows,

- Simulation-based evaluation: The submitted dialogue system is evaluated automatically by computing metrics based on dialogues with a user simulator. This evaluation comprises seven metrics, which are task success rate, average reward, average dialogue turn, precision, recall, F1, and booking rate. The task success rate is the major metric.
- Crowdworker-based evaluation: The submitted dialogue system has to interact with a real person and evaluated by the following four metrics: task success rate, average language understanding scores, average response appropriateness score, and average dialogue turn. The task success rate is the major metric.
- Effect of hierarchical context information: It is to measure the performance of each subcomponent in the NLU modules, i.e., domain-intent classification, slot tagging, and the overall performance.
- Ablation study: This evaluation demonstrates the effectiveness of other engineering strategies to this system. It comprises six metrics, which are task success rate, average reward, average dialogue turn, precision, recall, and F1.

Quantitative Results

Simulation-based evaluation In the ConvLab platform, the user simulator randomly generates a users goals to test the submitted system and automatically evaluates the performance. The results in Table 4 show that our HCEDS achieves the highest score in task success rate and the highest F1 score (0.93), 6.9% higher than the second ranked participant (0.87). From the results in Table 5, we observe that the major gain comes from the usage of hierarchical context. By examining the details, the HCEDS obtains significantly improvement in terms of average dialogue return and average turn number, i.e., average dialogue return of 61.56, 102% improvement from baseline, and average 7 turns per dialogue with 93.75% of booking rate are also far advanced than that of baseline.

Crowdworker-based evaluation Table 5 lists the final results, where our HCEDS attain the second place on the task success rate. Our HCEDS also achieves significantly better performance than the baseline in the evaluated four metrics. More specifically, the HCEDS achieves a 65.81% task success rate and a 16.6% improvement over the baseline system. The systems NLU score reached 3.538, an increase of 14.2% compared with the baseline. The response appropriateness score is 3.632, 2.1% higher than the baseline. The average number of dialogues was around 15, which was reduced by about 2 turns compared with 17 turns of the baseline. Overall, we have a significant improvement over the baseline in both NLU and the average rounds.

Effects of hierarchical context information

We compare the performance of our Hierarchical Context Enhanced NLU (HCENLU) with the three official baseline models (SVMLU, ONENET, and MILU) on domain-intent classification and slot labeling. Furthermore, we analyze the effects of hierarchical context information across token-level and sentence-level to help better understand our system.

As shown in Table 6, our model achieved an 85% F1 score for the overall performance, about 2-point higher than the best baseline model, MILU. In the domain-intent classification, our model achieves 88% of the F1 score, about 4-point higher than the MILU. In addition, we attain 83-84% F1 score in the slot labelling with 1-2 point higher than MILU. These improvements are majorly caused by the modeling of hierarchical context information. By further analyzing the impact of context information on different levels, we observe that

- We can attain 84% F1 score, 1-point overall improvement by adding the token level context information \((b + c)\) extracted by the BERT embeddings. More specifically, the F1 score of the domain-intent classification is 87%, a 3-point improvement than the baseline, MILU. The
Table 4: Final results of the DSTC-8 Automatic evaluation

| Rank | Team Submission ID | Success Rate | Return | Turns | Precision | Recall | F1 | Book Rate |
|------|--------------------|--------------|--------|-------|-----------|--------|----|-----------|
| N/A  | Baseline           | 63.40%       | 30.41  | 7.67  | 0.72      | 0.83   | 0.75| 86.37%    |
| 10   | 504569             | 52.20%       | 15.81  | 8.83  | 0.46      | 0.75   | 0.54| 76.38%    |
| 9    | 504524             | 54.00%       | 17.15  | 9.65  | 0.66      | 0.76   | 0.69| 72.42%    |
| 8    | 504502             | 55.20%       | 20.14  | 11.06 | 0.68      | 0.77   | 0.71| 71.87%    |
| 7    | 504666             | 56.60%       | 23.7   | 7.9   | 0.61      | 0.73   | 0.64| 75.71%    |
| 6    | 504529             | 58.00%       | 20.14  | 9.78  | 0.68      | 0.77   | 0.71| 75.11%    |
| 5    | 504430             | 79.40%       | 49.69  | 7.59  | 0.80      | 0.89   | 0.83| 87.02%    |
| 4    | 504641             | 80.60%       | 51.51  | 7.21  | 0.61      | 0.73   | 0.64| 75.55%    |
| 3    | 504563             | 88.60%       | 61.63  | 6.69  | 0.83      | 0.94   | 0.87| 96.39%    |
| 2    | 504429(ours)       | 88.80%       | 61.56  | 7.00  | 0.92      | 0.96   | 0.93| 93.75%    |

Table 5: Final results of the DSTC-8 HUMAN evaluation

| Rank | Team Submission ID | Success Rate | Language Understanding Score | Response Appropriateness Score | Turns |
|------|--------------------|--------------|-------------------------------|--------------------------------|-------|
| N/A  | Baseline           | 56.45%       | 3.097                         | 3.556                          | 17.543|
| 10   | 504502             | 23.30%       | 2.612                         | 2.65                           | 15.333|
| 9    | 504666             | 35.77%       | 2.944                         | 3.103                          | 21.128|
| 8    | 504582             | 43.56%       | 3.554                         | 3.446                          | 21.818|
| 7    | 504529             | 54.90%       | 3.784                         | 3.824                          | 14.968|
| 6    | 504569             | 62.91%       | 3.742                         | 3.815                          | 14.968|
| 5    | 504641             | 64.10%       | 3.547                         | 3.829                          | 16.906|
| 4    | 504565             | 65.09%       | 3.538                         | 3.840                          | 13.884|
| 3    | 504563             | 68.32%       | 4.149                         | 4.287                          | 19.507|
| 2    | 504429(ours)       | 68.32%       | 4.149                         | 4.287                          | 15.481|

The above results indicate that the context information in both token-level and sentence-level can help to improve the performance of domain-intent classification and slot tagging. Besides, intent-guided attention information is help for the domain-intent classification.

Table 6: Results of the NLU models on MultiWOZ

| Model       | Intent R | P | F | Tag R | P | F | Overall R | P | F |
|-------------|----------|---|---|-------|---|---|----------|---|---|
| SVMLU       | -        | - | - | -     | - | - | 47%      | 68%| 56%|
| OneNet      | -        | - | - | -     | - | - | 58%      | 71%| 64%|
| MBLU        | 86%      | 81%| 84%| 85%   | 80%| 82%| 85%      | 81%| 83%|
| HCENLU      | +b       | 88%| 86%| 87%  | 86%| 80%| 83%      | 86%| 82%| 84%|
| +b+c        | 88%      | 86%| 87%| 85%   | 80%| 82%| 86%      | 83%| 84%| 84%|
| +b+c+s4t    | 88%      | 87%| 87%| 86%   | 82%| 84%| 86%      | 84%| 85%| 85%|
| +b+c+s4t+a4i| 88%     | 87%| 88%| 85%   | 82%| 84%| 86%      | 84%| 85%| 85%|
| HCEDS(final)| +b+c+s4t+a4i | 88% | 87%| 88%  | 86%| 81%| 83%      | 86%| 83%| 85%|

Ablation study

The ablation study analyzes the effects of each module in the system in two ways. First, we replace one of the modules in
the official baseline model into modules in our system to analyze the effects of individual modules in our system. Then, we replace one module from the HCEDS into a module in the baseline system to analyze the impact of each module on our system.

Table 7 shows the results of the first way of ablation study. The HCENLU increases the target success rate from 64% to 68.4%, while SP increases the target success rate to 80.2%, a huge improvement at 16.4%. MINLG attains only 0.6% improvement and reduce the dialog length by 0.46 turns. In summary, the performance of the system is improved by incorporating the context information and gained significantly by SP.

Table 8 lists the ablation study results of the second investigation. If HCENLU is removed, the success rate will drop 9.4% while removing the SP module, the success rate drops 17%. By replacing the MINLG module, the system performance will drop about 1% while the length of the dialogue turns increases by about 0.5 rounds.

Qualitative Results
To help extensively understand the mechanism of the HCEDS, we present a success dialogue in table 9. Each row represents a round of dialogue between user simulator and system. The user simulator utters utterance according to a randomly chosen pre-defined user-goal and previous respond from the dialogue system. The dialogue is completed within a simulated environment. The seven turns of dialogue occur three domain-switches (turn 2-3, 3-4 and 4-5). The example shows the ability of our system to handle domain-switch in multi-domain dialogue.

In this paper, we describe our submitted Hierarchical Context Enhanced Dialogue System (HCEDS), a modular multi-domain dialogue system, for Task1 of the DSTC8-track1 challenge. Our proposed HCEDS explores the potential of hierarchical contextual information from a multi-domain dialogue system. The NLU module gains better understanding of utterances by modeling token-level and sentence-level context information, which significantly improves the performance of domain-intent classification and slot labelling on the MultiWOZ dataset, and there has been a significant accuracy raise lead by the engineering improvement in policy. It is worth noting that the HCEDS achieves the best performance in the automatic evaluation. Our system gets second place in the manual evaluation. This paper shed some lights in exploring the potential of contextual information for multi-domain dialogue systems.

References

[Budzianowski et al. 2018] Budzianowski, P.; Wen, T.-H.; Tseng, B.-H.; Casanueva, I.; Ultes, S.; Ramadan, O.; and Gašić, M. 2018. Multiwoz-a large-scale multi-domain wizard-of-oz dataset for task-oriented dialogue modelling. arXiv preprint arXiv:1810.00278

[Cuayáhuital, Keizer, and Lemon 2015] Cuayáhuital, H.; Keizer, S.; and Lemon, O. 2015. Strategic dialogue management via deep reinforcement learning. arXiv preprint arXiv:1511.08099

[DeVault, Leuski, and Sagae 2011] DeVault, D.; Leuski, A.; and Sagae, K. 2011. An evaluation of alternative strategies for implementing dialogue policies using statistical classification and hand-authored rules. In Proceedings of 5th Inter-
national Joint Conference on Natural Language Processing, 1341–1345.

[Devlin et al. 2018] Devlin, J.; Chang, M.-W.; Lee, K.; and Toutanova, K. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805

[Hochreiter and Schmidhuber 1997] Hochreiter, S., and Schmidhuber, J. 1997. Long short-term memory. Neural computation 9(8):1735–1780.

[Kim, Lee, and Stratos 2017] Kim, Y.-B.; Lee, S.; and Stratos, K. 2017. Onenet: Joint domain, intent, slot prediction for spoken language understanding. In 2017 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU), 547–553. IEEE.

[Kingma and Ba 2014] Kingma, D. P., and Ba, J. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

[LeCun et al. 1998] LeCun, Y.; Bottou, L.; Bengio, Y.; and Haffner, P. et al. 1998. Gradient-based learning applied to document recognition. Proceedings of the IEEE 86(11):2278–2324.

[Li et al. 2019] Lee, S.; Zhu, Q.; Takanobu, R.; Li, X.; Zhang, Y.; Zhang, Z.; Li, J.; Peng, B.; Li, X.; Huang, M.; et al. 2019. Convlab: Multi-domain end-to-end dialog system platform. arXiv preprint arXiv:1904.08637.

[Li et al. 2017] Li, X.; Chen, Y.-N.; Li, L.; Gao, J.; and Celikyilmaz, A. 2017. End-to-end task-completion neural dialogue systems. arXiv preprint arXiv:1703.01008.

[Luong, Pham, and Manning 2015] Luong, M.-T.; Pham, H.; and Manning, C. D. 2015. Effective approaches to attention-based neural machine translation. arXiv preprint arXiv:1508.04025.

[Mairesse et al. 2009] Mairesse, M.; Gasic, M.; Jurcicek, F.; Keizer, S.; Thomson, B.; Yu, K.; and Young, S. 2009. Spoken language understanding from unaligned data using discriminative classification models. In 2009 IEEE International Conference on Acoustics, Speech and Signal Processing, 4749–4752. IEEE.

[Mehri, Srinivasan, and Eskenazi 2019] Mehri, S.; Srinivasan, T.; and Eskenazi, M. 2019. Structured fusion networks for dialog. arXiv preprint arXiv:1907.10016.

[Miller et al. 2017] Miller, A. H.; Feng, W.; Fisch, A.; Lu, J.; Batra, D.; Bordes, A.; Parikh, D.; and Weston, J. 2017. Parlai: A dialog research software platform. arXiv preprint arXiv:1705.06476.

[Mrkšić et al. 2016] Mrkšić, N.; Séaghdha, D. O.; Wen, T.-H.; Thomson, B.; and Young, S. 2016. Neural belief tracker: Data-driven dialogue state tracking. arXiv preprint arXiv:1606.03777.

[Peng et al. 2017] Peng, B.; Li, X.; Li, L.; Gao, J.; Celikyilmaz, A.; Lee, S.; and Wong, K.-F. 2017. Composite task-completion dialogue policy learning via hierarchical deep reinforcement learning. arXiv preprint arXiv:1704.03084.

[Ramadan, Budzianowski, and Gašić 2018] Ramadan, O.; Budzianowski, P.; and Gašić, M. 2018. Large-scale multi-domain belief tracking with knowledge sharing. arXiv preprint arXiv:1807.06517.

[Rastogi, Hakkani-Tür, and Heck 2017] Rastogi, A.; Hakkani-Tür, D.; and Heck, L. 2017. Scalable multi-domain dialogue state tracking. In 2017 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU), 561–568. IEEE.

[Schatzmann et al. 2015] Schatzmann, J.; Weilhammer, K.; Stuttle, M.; and Young, S. 2006. A survey of statistical user simulation techniques for reinforcement-learning of dialogue management strategies. The knowledge engineering review 21(2):97–126.

[Sennrich, Haddow, and Birch 2015] Sennrich, R.; Haddow, B.; and Birch, A. 2015. Neural machine translation of rare words with subword units. arXiv preprint arXiv:1508.07909.

[Ultes et al. 2017] Ultes, S.; Barahona, L. M. R.; Su, P.-H.; Vandyke, D.; Kim, D.; Casanueva, I.; Budzianowski, P.; Mrkšić, N.; Wen, T.-H.; Gasic, M.; et al. 2017. Pydial: A multi-domain statistical dialogue system toolkit. In Proceedings of ACL 2017, System Demonstrations, 73–78.

[Walker, Rambow, and Rogati 2002] Walker, M. A.; Rambow, O. C.; and Rogati, M. 2002. Training a sentence planner for spoken dialogue using boosting. Computer Speech & Language 16(3-4):409–433.

[Wen et al. 2015a] Wen, T.-H.; Gasic, M.; Kim, D.; Mrksic, N.; Su, P.-H.; Vandyke, D.; and Young, S. 2015a. Stochastic language generation in dialogue using recurrent neural networks with convolutional sentence reranking. arXiv preprint arXiv:1508.01755.

[Wen et al. 2015b] Wen, T.-H.; Gasic, M.; Mrksic, N.; Su, P.-H.; Vandyke, D.; and Young, S. 2015b. Semantically conditioned lstm-based natural language generation for spoken dialogue systems. arXiv preprint arXiv:1508.01743.

[Wen et al. 2016] Wen, T.-H.; Vandyke, D.; Mrksic, N.; Gasic, M.; Rojas-Barahona, L. M.; Su, P.-H.; Ultes, S.; and Young, S. 2016. A network-based end-to-end trainable task-oriented dialogue system. arXiv preprint arXiv:1604.04562.

[Williams et al. 2013] Williams, J.; Raux, A.; Ramachandran, D.; and Black, A. 2013. The dialog state tracking challenge. In Proceedings of the SIGDIAL 2013 Conference, 404–413.

[Yan et al. 2017] Yan, Z.; Duan, N.; Chen, P.; Zhou, M.; Zhou, J.; and Li, Z. 2017. Building task-oriented dialogue systems for online shopping. In Thirty-First AAAI Conference on Artificial Intelligence.

[Yang et al. 2016] Yang, Z.; Yang, D.; Dyer, C.; He, X.; Smola, A.; and Hovy, E. 2016. Hierarchical attention networks for document classification. In Proceedings of the 2016 conference of the North American chapter of the association for computational linguistics: human language technologies, 1480–1489.