A Context-Aware Hierarchical BERT Fusion Network for Multi-turn Dialog Act Detection

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Abstract
The success of interactive dialog systems is usually associated with the quality of the spoken language understanding (SLU) task, which mainly identifies the corresponding dialog acts and slot values in each turn. By treating utterances in isolation, most SLU systems often overlook the semantic context in which a dialog act is expected. The act dependency between turns is non-trivial and yet critical to the identification of the correct semantic representations. Previous works with limited context awareness have exposed the inadequacy of dealing with complexity in multiturn user intents, which are subject to spontaneous change during turn transitions. In this work, we propose to enhance SLU in multi-turn dialogs, employing a context-aware hierarchical BERT fusion Network (CaBERT-SLU) to not only discern context information within a dialog but also jointly identify multiple dialog acts and slots in each utterance. Experimental results show that our approach reaches new state-of-the-art (SOTA) performances in two complicated multi-turn dialogue datasets with considerable improvements compared with previous methods, which only consider single utterances for multiple intents and slot filling.

Index Terms: context, multi-intent, human-computer interaction, task-oriented dialog, BERT

1. Introduction
With the recent success of service assistants such as Alexa, Cortana and Siri, research attempts to expanding spoken language understanding (SLU) applications are becoming ubiquitous [1]. In canonical task-oriented dialogs, SLU establishes so-called semantic frames by capturing semantics in terms of intents and slots from speech recognized utterances [2]. These intents specify goals which commit speakers to some course of actions, like requesting, informing or acknowledging with a series of semantic notions known as slots. In the full dialog scenario, we refer these intents for an utterance within a dialog turn as dialog acts [3]. In Table 1 as an example in Microsoft dialogue challenge dataset [4], each utterance or response may involve more than one dialog acts with or without specific targeted slots.

Within traditional SLU frameworks, such identification process is usually articulated as a single intent classification task coupled with a slot labeling task by dissecting a dialog into single utterances [5] [6]. While most works induce large success in modeling the separate or joint distribution from intents and slots [7] [8] [9] [10], systems trained with such independent locutionary sentences quickly suffer from the insufficiency of capturing comprehensive semantics as the dialog flows. Irregularity and high mutability of user utterances may make it more difficult to capture precise user intents, especially for colloquial or implicit utterances [11]. Moreover, in real world scenario, an utterance can be associated with more than one intent [7] [12] [13] [14]. Dominant SLU systems have adopted several techniques to model such sophisticated semantic natures. [14] first explored the joint multi-intent and slot-filling task by treating multiple intents as a single context vector, but not scalable to a larger number of intents. [13] proposed a SOTA model to exploit slot-intent relations with the graph attention.

However, these approaches trained with independent utterances may not be sufficient in detecting contextual natures of dialog acts within dialogs, especially with the multiple intent cases [4] [13]. First, the sequential dependency between acts are obvious in most dialog cases regardless of domains. For instance, in Table 1 we can see ‘Select’ usually comes after ‘Offer’, and ‘Select’s slot is usually one of ‘Offer’s slots. Second, in less stylized conversations, they usually exhibit a broader open set of less bounded purposes, subject to arbitrary changes during turn transitions [16]. For instance in utterance 4, user presents another requests for the price even after the confirmation is done, which may result from heuristics of the ‘Japanese Brasserie’ restaurant name, which sounds expensive. Without such correlation matching, interpretability is undermined for joint tasks without any contextual information. Although in pipeline-based frameworks [1], the resolution of contextual utterances is typically addressed in the next dialog management module (DM) [17], dissecting dialogs unnaturally may still open the door for significant cascade of errors by neglecting contexts.

To avert such error propagation, some end-to-end dialog systems [18] [19] have been proposed to directly bypass the necessity of tracing dialog acts. Nevertheless, they lead to lower...
1. We propose CaBERT-SLU, which is the first attempt to consider previous dialog history for joint multiple dialog act and turn-level information to identify multiple dialog acts and slots. Simply, CaBERT-SLU will extract both utterance-level slot values, which however may not be compatible with an unknown ontology such as restaurant names.

In this work, we present a context-aware hierarchical BERT fusion network (CaBERT-SLU) to exploit dialog history for joint tasks. Simply, CaBERT-SLU will extract both utterance and turn-level information to identify multiple dialog acts and exploit a slot tagger to predict slots during the entire dialog. Our contributions are as follows and the code is available in https://github.com/waynewu6250/CaBERT-SLU.

1. We propose CaBERT-SLU, which is the first attempt to consider previous dialog history for joint multiple dialog act and slot filling tasks, where previous SLU works usually isolate the utterances and only detect single dialog act only.
2. We demonstrate the effectiveness of context fusion attention in joint tasks with the ablation study and visualization.
3. Experimental results show that our model achieves SOTA performances over several competitive baselines.

2. Methodology

2.1. Problem Statement

Suppose we have a predefined dialog act label set $Y^a$ and a slot set $Y^s$, given a dialog $X = \{x_1, x_2, \ldots, x_T\}$ of total $T$ user utterances and system responses, we would like to detect multiple dialog acts and slots for each $x_t$. For dialog act detection, we formulate it as a multi-label classification problem where for each $x_t$, we aim to find multiple dialog acts $(y_{a,t}, y_{a,t+1}, \ldots, y_{a,t+N_a})$, $\forall y_{a,t} \in Y^a$, and $N_a$ is the total number of dialog acts of the sample $x_t$. And for the slot filling task, for each $x_t = \{w_1, w_2, \ldots, w_N\}$ with total $N$ words, we wish to learn a parameterized mapping function to map input words into corresponding slot tags $(y_{s,t}, y_{s,t+1}, \ldots, y_{s,t+N_s})$, $\forall y_{s,t} \in Y^s$.

2.2. BERT self-attentive encoder

As shown in Figure 1, our model consists of four functional layers. We first encode each sentence $x_t = \{w_1, w_2, \ldots, w_N\}$ in a dialog $X$ with a BERT encoder $BERT_u$ to obtain token-level representations $\{h_i^t, h_i^t, \ldots, h_t^i\}$. BERT [25] is a multi-layer transformer-based encoder containing multi-head self-attention layers. It sufficiently extracts the contextualized information for each word token with respect to overall utterance. For a dialog with $T$ sentences, such $T$ token-level hidden representations will be sent into both the downstream context fusion encoder and the slot tagger to respectively predict dialog acts and slots.

To further obtain the sentence representation $s_t$ of each utterance $x_t$ based on $\{h_t^1, h_t^2, \ldots, h_t^K\}$ and better consider the individual word importance, we follow the work in [26] to use a self-attentive network. At each time step $t$ at sentence $x_t$, we first feed each token-level hidden state $h_t^b$ into an affine transformation $(W, b_u)$, $h_t^b = Wh_t^b + b_u$. Then we use equation (1) to obtain score $\alpha_t^b$.

$$\alpha_t^b = \frac{e^{h_t^bT_wu}}{\sum_{w} e^{h_t^bT_wu}}$$

Then $\{\alpha_t^b\}$ represents the similarity scores between each $h_t^b$ and $K$ heads of learnable context vectors $u_w$ which indicate the global sentence views; for each head, we can get a sentence representation $s_t^b = \sum \alpha_t^b h_t^b$. Finally, we will concatenate all the heads for the final representation $s_t$.

2.3. Context fusion encoder

After obtaining the final sentence representation $S = \{s_1, s_2, \ldots, s_T\} \in \mathbb{R}^{T \times H_u}$ for a dialog, where $H_u$ is BERT hidden size, we combine $\{s_1, s_2, \ldots, s_T\}$ with a unidirectional transformer encoder, which is devised to model the contextual relevance information throughout $T$ sentences in the dialog. This context fusion encoder contains a stack of $N_l$ layers. There are a masked multi-head self-attention sublayer (Attention) and a point-wise fully connected feed-forward network (FFN) as shown in equation (2). It will first project $S$ with weight matrices: $W^Q, W^K, W^V \in \mathbb{R}^{H_u \times H_a}$ to be $S^Q = SW^Q, S^K = SW^K, S^V = SW^V$. Then each of them will be separated into $h$ heads, with each head $t$ to be $H_t \in \mathbb{R}^{T \times (H_a/h)}$, $H_a$ is the hidden size for the attention module. These $H_t$ will be sent into the self-attention layer.
Table 2: Main results for the joint task on two datasets. We report accuracy (ID Acc) for all intent exact match, F1 scores (ID F1) based on each intent calculation. We also report intent accuracy (IO Acc) and F1 score (IO F1) with models trained only on intent detection task. † indicates that Stack-Prop can only predict single intent which we solely report its ID/IO Acc. ‡ indicates the significant improvement of p-value < 0.05 compared to the previous best contextual baseline [22].

| Dataset     | MDC | SGD |
|-------------|-----|-----|
|             | ID F1 | ID Acc | SL F1 | ID F1 | ID Acc | SL F1 | IO F1 | IO Acc | IO F1 | IO Acc |
| Model       |      |       |       |      |       |       |       |       |       |       |
| Stack-Prop  | 12  | 92.99 | 80.18 | 89.65 | 82.69 | 80.91 | 75.41 | 86.33 | 98.59 | 89.73 |
| Joint MID-SF| 14  | 86.18 | 75.75 | 70.92 | 86.33 | 85.11 | 78.21 | 85.48 | 75.41 | 90.71 |
| AGIF        | 13  | 89.63 | 80.18 | 78.87 | 91.96 | 85.41 | 86.68 | 90.73 | 74.12 | 92.41 |
| ECA         | 24  | 87.88 | 77.84 | 69.20 | 93.65 | 93.11 | 80.00 | 87.75 | 77.66 | 95.78 |
| BERT        | 25  | 90.67 | 81.84 | 78.21 | 95.25 | 92.75 | 89.05 | 89.71 | 81.43 | 94.06 |
| BERT+SA     | 26  | 89.91 | 80.63 | 78.19 | 95.32 | 92.99 | 90.01 | 89.73 | 81.64 | 94.95 |
| BERT+CASA-NLU| 22 | 90.98 | 82.17 | 78.16 | 97.07 | 95.24 | 90.46 | 90.25 | 80.91 | 96.72 |
| CaBERT-SLU  |     | 91.26 | 83.05 | 79.64 | 99.14 | 98.59 | 95.71 | 90.81 | 82.69 | 98.92 |

\[
\begin{align*}
\text{Attention}(H^Q, H^K, H^V) &= \text{softmax}\left(\frac{H^Q(H^K)^T}{\sqrt{d}}\right)H^V \\
FFN(x) &= \max(0, xW_1 + b_1)W_2 + b_2 \\
C^l &= S + PE(S) \\
C^l &= FFN(\text{Attention}(C^{l-1}, C^{l-1}, C^{l-1}))
\end{align*}
\]

2.4. Global Recurrent Unit

We found out that the context fusion encoder could introduce the mutual interaction between each utterance, which may nevertheless be insufficient to capture the global sequential information as the dialog progresses. Thus, we apply an additional unidirectional LSTM layer upon the context fusion layer to supplement such global relations to obtain the final output states \(H_{act} \in \mathbb{R}^{T \times H_z}\), where \(H_z\) is the hidden size of LSTM.

\[
H_{act} = \text{LSTM}(C^{N})
\]

Then we can generate the logits \(\hat{y}_s = \sigma(H_{act}W_{act})\) by transforming \(H_{act}\) with \(W_{act} \in \mathbb{R}^{H_z \times |\mathcal{Y}|}\) and sigmoid function \(\sigma\). Finally we can have the dialog act detection objective as a binary cross entropy loss where \(N_s\) is number of samples, \(T\) is the max dialog length in samples and \(|\mathcal{Y}|=n\) is the number of total dialog acts:

\[
L_a := -\sum_{i=1}^{N_s} \sum_{t=1}^{T} \sum_{j=1}^{|\mathcal{Y}|} (y^{(i,a)}_t \log(\hat{y}^{(i,a)}_t) + (1 - y^{(i,a)}_t) \log(1 - \hat{y}^{(i,a)}_t))
\]

2.5. Slot Tagger

In addition to detecting dialog acts, we further detect the slots for each utterance in the dialog. Here we take the hidden representation \(H_{tok} = [h_1, h_2, \ldots, h_N]\) from \(BERT_v\) again. Then we concatenate \(H_{tok}\) with the dialog act context information \(H_{act}\) to be slot hidden states \(E_{slot} = H_{tok} \oplus H_{act}\). Then we use another BiLSTM as the slot-filling tagger and generate the logits for each token.

\[
H_{slot} = \text{BiLSTM}(E_{slot})
\]

\[
\hat{y}_s = \text{softmax}(H_{slot}W_{slot})
\]

Finally we can define the cross entropy loss as the objective:

\[
L_s := -\sum_{i=1}^{N_s} \sum_{t=1}^{T} \sum_{j=1}^{|\mathcal{Y}|} \sum_{k=1}^{|\mathcal{V}|} (y^{(i,a)}_{t,k} \log(\hat{y}^{(i,a)}_{t,k}))
\]

The final joint objective will be formulated as \(L_a + L_s\).

3. Experiments

3.1. Datasets

We evaluate our model on two multi-turn dialog datasets: Microsoft Dialogue Challenge dataset (MDC) [4] and Schema-Guided Dialogue dataset (SGD) [15]. MDC is a human-annotated conversation dataset in three domains (movie, restaurant, taxi). Each of them contains 2890, 4103, 3094 dialogs with total 11 acts and 50 slots. For each utterance, it is attached a human and a virtual assistant. These conversations span 20 domains, ranging from banks and events to media, travel and weather. We mainly adopt the user and system acts in each utterance for the dialog act detection and corresponding slots for slot filling. It has total 18 acts and 89 slots. We mainly split the training/validation/testing data with the ratio 0.70/0.10/0.2.

3.2. Experimental Setup

We compare our results with several competitive baselines: Stack-Prop [12] which uses two stacked encode-decoder structures for joint single intent and slot filling tasks. Joint MID-SF [14] which first considers multi-intent detection task in use of BiLSTMs, AGIF [13] which uses graph interactive framework to consider fine-grained information, ECA [24] which encodes context with LSTM encoder for joint task prediction. We also fine-tune BERT pretrained layers with several proposed work including a self-attentive layer (SA) from [26] and CASA-NLU which encodes context with DiSAN sentence2token [22].

For experimental setting, we exploit the pretrained BERT model with 12 layers of 768 hidden units and 12 self-attention heads. For the self-attentive layer, we use 4 heads of context vectors. For the context fusion vector, we set 6 transformer layers with 12 self-attention heads each.
Table 3: Ablation study on different components of CaBERT-SLU. We report accuracy (ID Acc) for all intents exact match and F1 scores (ID F1) based on the individual intent calculation; SL F1 for slot-filling F1 scores. We also report intent accuracy (IO Acc) and F1 score (IO F1) with models trained solely on intent detection without slot filling. SA: self-attentive layer, CF: context fusion layer.

| Dataset | Model | ID F1 | ID Acc | SL F1 | ID F1 | ID Acc | SL F1 | IO F1 | IO Acc | IO F1 | IO Acc | IO F1 | IO Acc |
|---------|-------|-------|--------|-------|-------|--------|-------|-------|--------|-------|--------|-------|--------|
| MDC     | BERT  | 90.67 | 81.84  | 78.23 | 95.23 | 92.75  | 89.65 | 89.71 | 81.83  | 94.96 | 92.63  |
|         | +LSTM | 90.83 | 82.10  | 78.79 | 98.61 | 97.78  | 89.65 | 90.55 | 82.13  | 98.45 | 97.55  |
|         | +SA+LSTM | 90.84 | 82.38  | 78.61 | 98.61 | 97.99  | 90.19 | 90.53 | 82.02  | 98.48 | 97.65  |
|         | +SA+CF | 90.89 | 82.59  | 79.81 | 98.94 | 98.19  | 95.53 | 90.82 | 81.83  | 98.82 | 98.01  |
| SGD     | CaBERT-SLU | 91.26 | 83.05  | 79.64 | 99.14 | 98.59  | 95.71 | 90.81 | 82.69  | 98.92 | 98.24  |

4. Results

4.1. Main Results

Table 2 shows the performance of CaBERT-SLU on joint tasks in two dialogue datasets, compared with several baseline models. Our model beats all baselines whether they are based on single utterances or BERT-related techniques, and achieves 1.1% and 3.5% increase in intent accuracy of two datasets than BERT+CASA-NLU [22]. We believe that the strong performance yielded by CaBERT-SLU pertains to the robust contextual information sharing both mutually and sequentially in multiple layers of masked self-attention. Without learning different weights of the dialog history to the current turn, previous approaches’ performances are significantly undermined. Also, it achieves 1.9% and 5.8% increase in slot F1 score, benefited from our model’s contextual sharing. We can also observe a slight increase overall by considering the joint task. We estimate the effectiveness of each module of CaBERT-SLU by conducting ablation experiments as shown in Table 3. We observe a slight drop of 0.60% without using self-attentive layer. And by incorporating both context fusion layer and global recurrence layer, it can boost the performance by overall roughly 1.5% and almost 7% in SGD slot filling task.

To explore performances within different domains of our model, we separate MDC based on three domains. As for SGD, since a single dialog may involve multiple domains, we instead sample SGD with three variations: (1) dialogs associated with the ‘restaurant’ domain (2) dialogs with only ‘single’ domain (3) dialogs with ‘multiple’ domains. In Table 4, we can observe that taxi and movie domains are much easier than restaurant domain which contribute more in joint scores. In SGD, we can see our method performs well regardless of how data is subsampled; especially outperforming on multi-domain dialogs. Our model also performs well in multiple domain for slot filling where context fusion may benefit domain transition of slots.

4.2. Attention Visualization

To further understand the mechanism of our context fusion encoder, we visualize the attention weights over the mean of heads at the last layer, as shown in Figure 2. In the example dialog, user first asks system to find a kid friendly place to eat. And the system asks about time, date and number of people at id 1 and 3. Then we can observe id 2 and 4 have more weights on their close previous neighbors, which indicate the sequential relation between request and inform. We can see id 3 of asking number of people may be related to kid friendly keyword at id 0. After system talks about options of restaurants at id 5, id 6 replies with more dependency based on it. To note, with masked self-attention, we only attend weights on previous contexts.

5. Conclusion

In this work, we introduce an effective model that composes a contextual hierarchical structure affiliated with BERT to reinforce the connection between dialog contexts, which is often ignored by recent SLU works. By exploiting such naturalness of dialog flow, it is capable of capturing necessary mentions in previous dialog history for current tasks. Experimental results show that our model achieves strong improvements over models without contextual awareness. We also achieve SOTA results in joint multi-intent detection and slot filling of two multi-turn dialog datasets, without sacrificing the mutual relations between SLU and DM, and further error propagation.
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