

An Efficient Approach to Encoding Context for Spoken Language Understanding

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Abstract

In task-oriented dialogue systems, spoken language understanding, or SLU, refers to the task of parsing natural language user utterances into semantic frames. Making use of context from prior dialogue history holds the key to more effective SLU. State of the art approaches to SLU use memory networks to encode context by processing multiple utterances from the dialogue at each turn, resulting in significant trade-offs between accuracy and computational efficiency. On the other hand, downstream components like the dialogue state tracker (DST) already keep track of the dialogue state, which can serve as a summary of the dialogue history. In this work, we propose an efficient approach to encoding context from prior utterances for SLU. More specifically, our architecture includes a separate recurrent neural network (RNN) based encoding module that accumulates dialogue context to guide the frame parsing sub-tasks and can be shared between SLU and DST. In our experiments, we demonstrate the effectiveness of our approach on dialogues from two domains. Index Terms: spoken language understanding, dialogue systems, slot-filling, natural language understanding

1. Introduction

Task-oriented dialogue systems assist users with accomplishing tasks, such as making restaurant reservations or booking flights, by interacting with them in natural language. The capability to identify task-specific semantics is a key requirement for these systems. This is accomplished in the spoken language understanding (SLU) module, which typically parses natural language user utterances into semantic frames, composed of user intent, dialogue acts and slots [1], that can be processed by downstream dialogue system components. An example semantic frame is shown for a restaurant reservation query in Figure 1. It is common to model intent, dialogue act and slot prediction jointly [2, 3, 4, 5], which is a direction we follow.

Much prior research into SLU has focused on single-turn language understanding, where the system receives only the user utterance and, possibly, external contextual features such as knowledge base annotations [6] and semantic context from the frame [7], as inputs. However, task-oriented dialogue commonly involves the user and the system indulging in multiple turns of back-and-forth conversation in order to achieve the user goal. Multi-turn SLU presents different challenges, since the user and the system may refer to entities introduced in prior dialogue turns, introducing ambiguity. For example, depending on the context, "three" could indicate a date, time, number of tickets or restaurant rating. Context from previous user and system utterances in multi-turn dialogue has been shown to help resolve these ambiguities [8, 9]. While initial work in this direction used only the previous system turn for context, the advent of deep learning techniques, memory networks [10] in particular, facilitated incorporating context from the full dialogue history.

System:	Which restaurant and for how many?										
Dialogue Acts:	<pre>request(#), request(rest)</pre>										
User:	Table	for	two	at	Olive	Garden					
	\downarrow	\downarrow	\downarrow	\downarrow	\downarrow	\downarrow					
Slot:	0	0	B-#	0	B-rest	I-rest					
Intent:	reserve_restaurant										
Dialogue Acts:	<pre>inform(#), inform(rest)</pre>										

Figure 1: An example semantic frame with slot, intent and dialogue act annotations, following the IOB tagging scheme.

In essence, memory network-based approaches to multiturn SLU store prior user and system utterances and, at the current turn, encode these into embeddings, using RNNs or otherwise. These memory embeddings are then aggregated to obtain the context vector which is used to condition the SLU output at the current turn. This aggregation step could use an attention mechanism based on cosine similarity with the user utterance embedding [11]. Other approaches account for temporal order of utterances in the memory by using an RNN for aggregation [12] or decaying attention weights with time [13].

Although improving accuracy, using memory networks for encoding context is not computationally efficient for two reasons. First, at each turn, they process multiple history utterances to obtain the SLU output. Secondly, dialogue context could potentially be gleaned from existing dialogue system components such as the dialogue state tracker [14, 15, 16]. Using a separate SLU-specific network instead of reusing the context from DST duplicates computation. Furthermore, such approaches work with the natural language representation of the system utterance to have a consistent representation with user turns, while ignoring the system dialogue acts, which contain the same information but are more structured and have a smaller vocabulary.

In this work, we investigate some effective approaches to encoding dialogue context for SLU. Our contributions are twofold. First, we propose a novel approach to encoding system dialogue acts for SLU, substituting the use of system utterances, which allows reuse of the dialogue policy manager's output to obtain context. Second, we propose an efficient mechanism for encoding dialogue context using hierarchical recurrent neural networks which processes a single utterance at a time, yielding computational gains without compromising performance. Our representation of dialogue context is similar to those used in dialogue state tracking models [17, 18, 19], thus enabling the sharing of context representation between SLU and DST.

The rest of this paper is organized as follows: Section 2 describes the overall architecture of the model. This section also formally describes the different tasks in SLU and outlines their implementation. Section 3 presents the setup for training and evaluation of our model. We conclude with experimental results and discussion.

2. Approach

Let a dialogue be a sequence of T turns, each turn containing a user utterance U^t and a set of dialogue acts A^t corresponding to the preceding system utterance. Figure 2 gives an overview of our model architecture. For a new turn t, we use the system act encoder (Section 2.1) to obtain a vector representation a^t of all system dialogue acts A^t . We also use the utterance encoder (Section 2.2) to generate the user utterance encoding u^t by processing the user utterance token embeddings x^t .

The dialogue encoder (Section 2.3) summarizes the content of the dialogue by using a^t , u^t , and its previous hidden state s^{t-1} to generate the dialogue context vector o^t , and also update its hidden state s^t . The dialogue context vector is then used for user intent classification and dialogue act classification (Section 2.4). The utterance encoder also generates updated token embeddings, which are used by the slot tagger (Section 2.5) to identify the slot values present in the user utterance.

Both the utterance encoder and slot tagger use bidirectional RNNs. In addition to the aforementioned inputs, both RNNs allow for additional inputs (positions A and C in Figure 2) and external initialization of hidden states (positions B and D in Figure 2), to incorporate context in our model. In the following sections, we describe each of these components in detail.

2.1. System Act Encoder

The system act encoder encodes the set of dialogue acts A^t at turn t into a vector a^t invariant to the order in which acts appear. This contrasts with a system utterance-based representation, which imposes an implicit ordering on the underlying acts.

Each system dialogue act contains an act type and optional slot and value parameters. We categorize the dialogue acts into two broad types - acts with an associated slot (and possibly a slot value i.e. request (time), negate (time=`6 pm')), and acts without (e.g. greeting). Note that the same dialogue act can appear in the dialogue with or without an associated slot (negate (time=`6 pm') versus negate).

For each slot type s in our slot vocabulary, we define a binary vector $a_{slot}^t(s)$ of size $|A_{sys}|$, where A_{sys} is the set of all system act types, indicating the presence of each system act type with that slot associated, ignoring slot values for tractability. Similarly, we define a binary vector a_{ns}^t of the same size $|A_{sys}|$ indicating the presence of each system act without any slot associated. For each slot s, we also define an embedding e_s . The final encoding a_t is obtained from these vectors after a shared feedforward layer on the slot-associated act features, followed by averaging over the set of slots S^t mentioned so far, concatenating with the no-slot act features and a second feedforward layer, as in equations 1 - 4. Parameters $W_1^a, W_2^a, b_1^a, b_2^a$ and slot embeddings e_s are trainable; \oplus denotes concatenation.

$$a'^{t}_{slot}(s) = a^{t}_{slot}(s) \oplus e_{s} \tag{1}$$

$${a''}_{slot}^{t}(s) = ReLU(W_1^a \cdot {a'}_{slot}^t(s) + b_1^a)$$
(2)

$$a_{comb}^{t} = \left(\frac{1}{|S^{t}|} \sum_{s \in S^{t}} {a''}_{slot}^{t}(s)\right) \oplus a_{ns}^{t}$$
(3)

$$a^t = ReLU(W_2^a \cdot a_{comb}^t + b_2^a) \tag{4}$$

2.2. Utterance Encoder

The user utterance encoder takes in the list of user utterance tokens as input. Special tokens SOS and EOS are added at the beginning and end of the token list. Let $x^t = \{x_m^t \in \mathbb{R}^{u_d}, \forall 0 \leq m < M^t\}$ denote the utterance token embeddings, M^t being the number of tokens in the user utterance for turn t. We use a single layer bi-directional RNN [20] using GRU cell [21] with state size d_u to encode the user utterance.

$$u^t, u^t_o = BRNN_{GRU}(x^t) \tag{5}$$

The user utterance encoder outputs embedded representations $u^t \in \mathbb{R}^{2d_u}$ of the user utterance and $u^t_o = \{u^t_{o,m} \in \mathbb{R}^{2d_u}, 0 \leq m < M^t\}$ of the individual utterance tokens, obtained by concatenating the final states and the intermediate outputs of the forward and backward RNNs respectively.

2.3. Dialogue Encoder

The dialogue encoder incrementally generates the embedded representation of the dialogue context at every turn. We implement the dialogue encoder using a unidirectional GRU RNN, with each timestep corresponding to a dialogue turn. As shown in Figure 2, it takes $a^t \oplus u^t$ and its previous state s^{t-1} as inputs and outputs the updated state s^t and the encoded representation of the dialogue context o^t (identical for a GRU RNN). This method of encoding context is more efficient than other state of the art approaches like memory networks which process multiple utterances from the history to process each turn.

2.4. Intent and Dialogue Act Classification

The user intent helps to identify the APIs/databases which the dialogue system should interact with. Intents are predicted at each turn so that a change of intent during the dialogue can be detected. We assume that each user utterance contains a single intent and predict the distribution over all intents at each turn, p_i^t , using equation 6. On the other hand, dialogue act classification is defined as a multi-label binary classification problem to model the presence of multiple dialogue acts in an utterance. Equation 7 is used to calculate p_a^t , where $p_a^t(k)$ is the probability of presence of dialogue act k in turn t.

$$p_i^t = softmax(W_i \cdot o^t + b_i) \tag{6}$$

$$p_a^t = sigmoid(W_a \cdot o^t + b_a) \tag{7}$$

In the above equations $\dim(p_i^t) = |I|$, $W_i \in \mathbb{R}^{d \times |I|}$, $W_a \in \mathbb{R}^{d \times |A_u|}$, $b_i \in \mathbb{R}^{|I|}$, and $b_a \in \mathbb{R}^{|A_u|}$, I and A_u denoting the user intent and dialogue act vocabularies respectively and $d = \dim(o^t)$. During inference, we predict $argmax(p_i^t)$ as the intent label and all dialogue acts with probability greater than t_u are associated with the utterance, where $0 < t_u < 1.0$ is a hyperparameter tuned using the validation set.

2.5. Slot Tagging

Slot tagging is the task of identifying the values for different slots present in the user utterance. We use the IOB (inside-outside-begin) tagging scheme (Figure 1) to assign a label to each token [22]. The slot tagger takes the token embeddings output by the utterance encoder as input and encodes them using a bidirectional RNN [20] using LSTM cell [23] with hidden state size d_s to generate token embeddings $s_o^t = \{s_{o,m}^t \in \mathbb{R}^{2d_s}, 0 \le m < M^t, M^t$ being the number of user utterance tokens in turn t. We use an LSTM cell instead of a GRU because it gave better results on the validation set. For the m^{th} token, we use the token vector $s_{o,m}^t$ to obtain the distribution across all 2|S| + 1 IOB slot labels using equation 8, |S| being the total number of slot types. During inference, we predict $argmax(p_{s,m}^t)$ as the slot label for the m^{th} token.

$$p_{s,m}^t = softmax(W_s \cdot s_{o,m}^t + b_s) \tag{8}$$



Figure 2: A generalized hierarchical recurrent neural network for joint prediction of user intent, dialogue acts (Section 2.4) and slot spans (Section 2.5). Context vectors can be fed as additional RNN inputs (positions A and C) or can be used to initialize the RNN hidden states (positions B and D).

3. Experiments

We use two representations of dialogue context: the dialogue encoding vector o^{t-1} encodes all turns prior to the current turn and the system intent vector a^t encodes the current turn system utterance. Thus, o^{t-1} and a^t together encode the entire conversation observed till the user utterance. These vectors can be fed as inputs at multiple places in the SLU model. In this work, we identify four positions to feed context i.e. positions A through D in Figure 2. Positions A and C feed context vectors as additional inputs at each RNN step whereas positions B and D use the context vectors to initialize the hidden state of the two RNNs after a linear projection to the hidden state dimension. We experiment with the following configurations for integrating dialogue context in our framework:

- a^t only, No DE: We feed a^t, the system act encoding, in one of positions A-D, omit the dialogue encoder, and instead use u^t, the utterance encoder's final state, for intent and act prediction. The best model for this configuration, as evaluated on the validation set, had a^t fed in position B, and test set results for this model are reported in row 7 of Table 1.
- 2. a^t only: We feed a^t into the dialogue encoder, and to one of the positions A-D. Row 8 of Table 1 contains results for the best model for this configuration, which had a^t fed in position D of the slot tagger.
- 3. o^{t-1} only: We feed a^t into the dialogue encoder and o^{t-1} , the dialogue encoding from the previous turn, into the slot tagger at positions C or D. Row 9 of Table 1 shows results for the best model with o^{t-1} fed in position D.
- 4. $a^t and o^{t-1}$: We feed a^t into the dialogue encoder, and o^{t-1} and a^t independently into one of positions C and D, 4 combinations in total. Row 10 of Table 1 shows results for the best model with a^t fed in position C and o^{t-1} in position D.

3.1. Dataset

We obtain dialogues from the Simulated Dialogues dataset ¹, described in [24]. The dataset has dialogues from restaurant (Sim-R, 11234 turns in 1116 training dialogues) and movie (Sim-M, 3562 turns in 384 training dialogues) domains and a total of three intents. The dialogue and types, with 2 slot types and 21 user dialogue act types, with 2 slot types and 12 dialogue acts shared between Sim-R and Sim-M. One challenging aspect of this dataset is the prevalence of unseen entities. For instance, only 13% of the movie names in the validation and test sets are also present in the training set.

3.2. Baselines

We compare our models' performance with the following four baseline models:

- 1. *NoContext:* A two-layer stacked bidirectional RNN using GRU and LSTM cells respectively, and no context.
- 2. *PrevTurn:* This is similar to the *NoContext* model. with a different bidirectional GRU layer encoding the previous system turn, and this encoding being input to the slot tagging layer of encoder i.e. position C in Figure 2.
- 3. *MemNet:* This is the system from [11], using cosine attention. For this model, we report metrics with models trained with memory sizes of 6 and 20 turns. A memory size of 20, while making the model slower, enables it to use the entire dialogue history for most of the dialogues.
- 4. *SDEN:* This is the system from [12] which uses a bidirectional GRU RNN for combining memory embeddings. We report metrics for models with memory sizes 6 and 20.

¹The dataset is available at http://github.com/google-researchdatasets/simulated-dialogue

Table 1: *SLU* results on test sets with baselines and our proposed architecture variants, when trained on Sim-M + Sim-R. For each dataset, the columns indicate the intent accuracy, dialogue act F1 score, slot chunk F1 score and frame accuracy, in that order. The Config column indicates the best obtained config for feeding context vectors for each experiment.

Model	Co	onfig	Sim-R Results				Sim-M Results				Overall Results			
			Intent	Act	Slot	Frame	Intent	Act	Slot	Frame	Intent	Act	Slot	Frame
	a^t	o^{t-1}	Acc	F1	F1	Acc	Acc	F1	F1	Acc	Acc	F1	F1	Acc
1. NoContext	-	-	83.61	87.13	94.24	65.51	88.51	93.49	86.91	62.17	84.76	89.03	92.01	64.56
2. PrevTurn	-	-	99.37	90.10	94.96	86.93	99.12	93.58	88.63	77.27	99.31	91.13	93.06	84.19
3. MemNet-6	-	-	99.75	92.90	94.42	88.33	99.12	95.71	89.76	79.11	99.68	93.74	93.03	85.71
4. MemNet-20	-	-	99.67	95.67	94.28	89.52	98.76	96.25	90.70	80.35	99.29	95.85	93.21	86.92
5. SDEN-6	-	-	99.76	93.14	95.83	88.74	99.74	95.02	88.60	79.11	99.76	93.70	93.66	86.01
6. SDEN-20	-	-	99.84	94.43	94.81	89.46	99.60	97.56	90.93	82.55	99.81	95.38	93.65	87.50
7. a^t only, No DE	B	-	99.62	93.21	95.53	87.63	99.12	96.00	87.30	75.44	99.48	94.04	93.07	84.17
8. a^t only	D	-	99.98	95.42	95.38	89.26	99.71	96.35	91.58	83.36	99.92	95.70	94.22	87.58
9. o^{t-1} only	-	D	99.83	94.44	94.18	87.63	99.27	96.66	91.88	86.80	99.67	95.11	93.46	87.40
10. a^t and o^{t-1}	C	D	99.65	92.71	94.70	87.54	99.27	96.11	93.73	86.88	99.54	93.74	94.40	87.35

3.3. Training and Evaluation

We use sigmoid cross entropy loss for dialogue act classification (since it is modeled as a multilabel binary classification problem) and softmax cross entropy loss for intent classification and slot tagging. During training, we minimize the sum of the three constituent losses using the ADAM optimizer [25] for 150k training steps with a batch size of 10 dialogues.

To improve model performance in the presence of out of vocabulary (OOV) tokens arising from entities not present in the training set, we randomly replace tokens corresponding to slot values in user utterance with a special OOV token with a value dropout probability that linearly increases during training.

To find the best hyperparameter values, we perform grid search over the token embedding size ($\in \{64, 128, 256\}$), learning rate ($\in [0.0001, 0.01]$), maximum value dropout probability ($\in [0.2, 0.5]$) and the intent prediction threshold ($\in \{0.3, 0.4, 0.5\}$), for each model configuration listed in Section 3. The utterance encoder and slot tagger layer sizes are set equal to the token embedding dimension, and that of the dialogue encoder to half this dimension. In Table 1, we report intent accuracy, dialogue act F1 score, slot chunk F1 score [22] and frame accuracy on the test set for the best runs for each configuration in Section 3 based on frame accuracy on the combined validation set, to avoid overfitting. A frame is considered correct if its predicted intent, slots and acts are all correct.

4. Results and Discussion

Table 1 compares the baseline models with different variants of our model. We observe that our models compare favorably to the state-of-the-art MemNet and SDEN baselines. The use of context plays a crucial role across all datasets and tasks, especially for intent and dialogue act classification, giving an improvement of ~15% and ~5% respectively across all configurations. For all subsequent discussion, we concentrate on frame accuracy since it summarizes the performance across all tasks.

An important consideration is the computational efficiency of the compared appraoches: memory network-based models are expensive to run, since they process multiple utterances from the dialogue history at every turn. In contrast, our approach only adds a two-layer feedforward network (the system act encoder) and one step of a GRU cell (for the dialogue encoder) per turn to encode all context. Empirically, MemNet-6 and MemNet-20 experiments took roughly 4x and 12x more time to train respectively than our slowest model containing both the system act encoder and the dialogue encoder, on our training setup. SDEN runs are slower than their MemNet counterparts since they use RNNs for combining memory embeddings. In addition to being fast, our models generalize better on the smaller Sim-M dataset, suggesting that memory networkbased models tend to be more data intensive.

Two interesting experiments to compare are rows 2 and 7 i.e. "PrevTurn" and " a^t only, No DE"; they both use context only from the previous system utterance/acts, discarding the remaining turns. Our system act encoder, comprising only a twolayer feedforward network, is in principle faster than the bidirectional GRU that "PrevTurn" uses to encode the system utterance. This notwithstanding, the similar performance of both models suggests that using system dialogue acts for context is a good alternative to using the corresponding system utterance.

Table 1 also lists the best configurations for feeding context vectors a^t and o^{t-1} . In general, we observe that feeding context vectors as initial states to bidirectional RNNs (i.e. position D for slot tagging plus a side input to the dialogue encoder) yields better results than feeding them as additional inputs at each RNN step (positions C and A). This may be caused by the fact that our context vectors do not vary with the user utterance tokens, because of which introducing them repeatedly is likely redundant. For each experiment in Section 3, the differences between the varying context position combinations are statistically significant, as determined by McNemar's test with p < 0.05.

Another interesting observation is that using o^{t-1} as compared to a^t as additional context for the slot tagger does not improve slot tagging performance. This indicates a strong correspondence between the slots present in the system acts and those mentioned in the user utterance i.e. the user is often responding directly to the immediately prior system prompt, thereby reducing the dependence on context from the previous turns for the slot tagging task.

To conclude, we present a fast and efficient approach to encoding context for SLU. Avoiding the significant per-turn overhead of memory networks, our method accumulates dialogue context one turn at a time, resulting in a faster and more generalizable model without any loss in accuracy. We also demonstrate that using system dialogue acts is an efficient alternative to using system utterances for context.

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