Abstract

Dialogue state tracking, which estimates user goals and requests given the dialogue context, is an essential part of task-oriented dialogue systems. In this paper, we propose the Global-Locally Self-Attentive Dialogue State Tracker (GLAD), which learns representations of the user utterance and previous system actions with global-local modules. Our model uses global modules to share parameters between estimators for different types (called slots) of dialogue states, and uses local modules to learn slot-specific features. We show that this improves tracking of rare states and achieves state-of-the-art performance on the WoZ and DSTC2 state tracking tasks. GLAD obtains 88.1% joint goal accuracy and 97.1% request accuracy on WoZ, outperforming prior work by 3.7% and 5.5%. On DSTC2, our model obtains 74.5% joint goal accuracy and 97.5% request accuracy, outperforming prior work by 1.1% and 1.0%.

1 Introduction

Task-oriented dialogue systems can reduce operating costs by automating processes such as call center dispatch and online customer support. Moreover, when combined with automatic speech recognition systems, task-oriented dialogue systems provide the foundation of intelligent assistants such as Amazon Alexa, Apple Siri, and Google Assistant. In turn, these assistants allow for natural, personalized interactions with users by tailoring natural language system responses to the dialogue context. Dialogue state tracking (DST) is a crucial part of dialogue systems (Young et al., 2013). In DST, a dialogue state tracker estimates the state of the conversation using the current user utterance and the conversation history. The dialogue system then uses this estimated state to plan the next action and respond to the user. A state in DST typically consists of a set of requests and joint goals. Consider the task of restaurant reservation as an example. During each turn, the user informs the system of particular goals they would like to achieve (e.g. inform(food=french)), or request for more information from the system (e.g. request(address)). The set of goal and request slot-value pairs (e.g. (food, french), (request, address)) given during a turn are referred to as the turn goal and turn request. The joint goal is the set of accumulated turn goals up to the current turn. Figure 1 shows an example dialogue with annotated turn states, in which the user reserves a restaurant.

Traditional dialogue state trackers rely on Spoken Language Understanding (SLU) systems (Henderson et al., 2012) in order to understand user utterances. These trackers accumulate errors from the SLU, which sometimes do not have the necessary dialogue context to interpret the user utterances. Subsequent DST research forgo the SLU and directly infer the state using the conversation history and the user utterance (Henderson et al., 2014b; Zilka and Jurcicek, 2015: Mrkšić et al., 2015). These trackers rely on hand-crafted semantic dictionaries and delexicalization — the anonymization of slots and values using generic tags — to achieve generalization. Recent work by Mrkšić et al. (2017) apply representation learning using convolutional neural networks to learn features relevant for each state as opposed to hand-crafting features.

A key problem in DST that is not addressed by existing methods is the extraction of rare slot-value pairs that compose the state during each
Where would you go to eat in the south part of town?

I just want to eat at a cheap restaurant in the south part of town. What food types are available, can you also provide some phone numbers?

I found two restaurants serving cheap food. Would you prefer Portuguese or Chinese food?

Either is fine, can I have the phone number please?

Thank you very much.

Figure 1: An example dialogue from the WoZ restaurant reservation corpus. Dashed lines divide turns in the dialogue. A turn contains an user utterance (purple), followed by corresponding turn-level goals and requests (blue). The system then executes actions (yellow), and formulates the result into a natural language response (yellow).

In this work, we propose the Global-Locally Self-Attentive Dialogue State Tracker (GLAD), a new state-of-the-art model for dialogue state tracking. In contrast to previous work that estimate each slot-value pair independently, GLAD uses global modules to share parameters between estimators for each slot and local modules to learn slot-specific feature representations. We show that by doing so, GLAD generalizes on rare slot-value pairs with few training examples. GLAD achieves state-of-the-art results of 88.1% goal accuracy and 97.1% request accuracy on the WoZ dialogue state tracking task (Wen et al., 2017), outperforming prior best by 3.7% and 5.5%. On DSTC2 (Henderson et al., 2014a), we achieve 74.5% goal accuracy and 97.5% request accuracy, outperforming prior best by 1.1% and 1.0%. We release an implementation of our model along with a Docker image of our experiment setup for reproducibility.

2 Global-Locally Self-Attentive Dialogue State Tracker

One formulation of state tracking is to predict the turn state given an user utterance and previous system actions (Williams and Young, 2007). Like previous methods (Henderson et al., 2014b; Wen et al., 2017; Mrkšić et al., 2017), GLAD decomposes the multi-label state prediction problem into a collection of binary prediction problems by using a distinct estimator for each slot-value pair that make up the state. Hence, we describe GLAD with respect to a slot-value pair that is being predicted by the model.

Shown in Figure 2, GLAD is comprised of an encoder module and a scoring module. The encoder module consists of separate global-locally self-attentive encoders for the user utterance, the previous system actions, and the slot-value pair under consideration. The scoring module consists of two scorers. One scorer considers the contribution from the utterance while the other considers the contribution from previous system actions.

2.1 Global-Locally Self-Attentive Encoder

We begin by describing the global-locally self-attentive encoder, which makes up the encoder module. DST datasets tend to be small relative to their state space in that many slot-value pairs rarely occur in the dataset. Because each state is comprised of a set of slot-value pairs, many of

1 https://github.com/salesforce/glad
I just want to eat at a cheap restaurant in the south part of town. What food types are available, can you also provide some phone numbers?

Figure 2: The Global-Locally Self-Attentive Dialogue State Tracker.

Consider the process of encoding a sequence with respect to a particular slot \( s \). Let \( n \) denote the number of words in the sequence, \( d_{\text{emb}} \) the dimension of the embeddings, and \( X \in \mathbb{R}^{n \times d_{\text{emb}}} \) the word embeddings corresponding to words in the sequence. We produce a global encoding \( H^g \) of \( X \) using a global bidirectional LSTM.

\[
H^g = \text{biLSTM}^g(X) \in \mathbb{R}^{n \times d_{\text{rnn}}}
\]  

(1)

where \( d_{\text{rnn}} \) is the dimension of the LSTM state. We similarly produce a local encoding \( H^s \) of \( X \), taking into account the slot \( s \), using a local bidirectional LSTM.

\[
H^s = \text{biLSTM}^s(X) \in \mathbb{R}^{n \times d_{\text{rnn}}}
\]  

(2)

The outputs of the two LSTMs are combined through a mixture function to yield a global-local encoding \( H \) of \( X \).

\[
H = \beta^s H^s + (1 - \beta^s) H^g \in \mathbb{R}^{n \times d_{\text{rnn}}}
\]  

(3)

Here, the scalar \( \beta^s \) is a learned parameter between 0 and 1 that is specific to the slot \( s \). Next, we compute a global-local self-attention context \( c \) over \( H \). Self-attention, or intra-attention, is an effective method to compute summary context over variable-length sequences for natural language processing tasks (Cheng et al., 2016; Vaswani et al., 2017; He et al., 2017; Lee et al., 2017). In our case, we use a global self-attention module to compute an attention context useful for general-purpose state tracking, as well as a local self-attention module to compute a slot-specific attention context.
For each \( i \)th element \( H_i \), we compute a scalar global self-attention score \( a^g_i \) which is subsequently normalized across all elements using a softmax function.

\[
a^g_i = W^g H_i + b^g \in \mathbb{R} \tag{4}
\]

\[
p^g_i = \text{softmax}(a^g_i) \in \mathbb{R}^n \tag{5}
\]

The global self-attention context \( c^g \) is then the sum of each element \( H_i \), weighted by the corresponding normalized global self-attention score \( p^g_i \).

\[
c^g = \sum_i p^g_i H_i \in \mathbb{R}^{d_{	ext{rnn}}} \tag{6}
\]

We similarly compute the local self-attention context \( c^s \).

\[
a^s_i = W^s H_i + b^s \in \mathbb{R} \tag{7}
\]

\[
p^s_i = \text{softmax}(a^s_i) \in \mathbb{R}^n \tag{8}
\]

\[
c^s = \sum_i p^s_i H_i \in \mathbb{R}^{d_{	ext{rnn}}} \tag{9}
\]

The global-local self-attention context \( c \) is the mixture

\[
c = \beta^s c^s + (1 - \beta^s) c^g \in \mathbb{R}^{d_{	ext{rnn}}} \tag{10}
\]

For ease of exposition, we define the multi-value encode function \( \text{encode} (X) \).

\[
\text{encode} : X \rightarrow H, c \tag{11}
\]

This function maps the sequence \( X \) to the encoding \( H \) and the self-attention context \( c \).

### 2.2 Encoding module

Having defined the global-locally self-attentive encoder, we now build representations for the user utterance, the previous system actions, and the slot-value pair under consideration. Let \( U \) denote word embeddings of the user utterance, \( A_j \) denote those of the \( j \)th previous system action (e.g. request \{ price range \}), and \( V \) denote those of the slot-value pair under consideration (e.g. \text{food} = \text{french}). We have

\[
H^\text{utt}, c^\text{utt} = \text{encode} (U) \tag{12}
\]

\[
H^\text{act}_j, C^\text{act}_j = \text{encode} (A_j) \tag{13}
\]

\[
H^\text{val}, c^\text{val} = \text{encode} (V) \tag{14}
\]

### 2.3 Scoring module

Intuitively, we can determine whether the user has expressed the slot-value pair under consideration by examining two input sources. The first source is the user utterance, in which the user directly states the goals and requests. An example of this is the user saying “how about a French restaurant in the centre of town?” after the system asked “how may I help you?” To handle these cases, we determine whether the utterance specifies the slot-value pair. Namely, we attend over the user utterance \( H^\text{utt} \), taking into account the slot-value pair being considered \( c^\text{val} \), and use the resulting attention context \( q^\text{utt} \) to score the slot-value pair.

\[
a^\text{utt}_i = (H^\text{utt}_i)^T c^\text{val} \in \mathbb{R} \tag{15}
\]

\[
p^\text{utt} = \text{softmax}(a^\text{utt}) \in \mathbb{R}^m \tag{16}
\]

\[
q^\text{utt} = \sum_i p^\text{utt}_i H^\text{utt}_i \in \mathbb{R}^{d_{	ext{rnn}}} \tag{17}
\]

\[
y^\text{utt} = W^\text{utt} q^\text{utt} + b \in \mathbb{R} \tag{18}
\]

where \( m \) is the number of words in the user utterance. The score \( y^\text{utt} \) indicates the degree to which the value was expressed by the user utterance.

The second source is the previous system actions. This source is informative when the user utterance does not present enough information and instead refers to previous system actions. An example of this is the user saying “yes”, after the system asked “would you like a restaurant in the centre of town?” To handle these cases, we examine previous actions after considering the user utterance. First, we attend over the previous action representations \( C^\text{act} = [C_1^\text{act} \ldots C_l^\text{act}] \), taking into account the current user utterance \( c^\text{utt} \). Here, \( l \) is the number of previous system actions. Then, we use the similarity between the attention context \( q^\text{act} \) and the slot-value pair \( c^\text{val} \) to score the slot-value pair.

\[
a^\text{act}_j = (C^\text{act}_j)^T c^\text{utt} \in \mathbb{R} \tag{19}
\]

\[
p^\text{act} = \text{softmax}(a^\text{act}) \in \mathbb{R}^{l+1} \tag{20}
\]

\[
q^\text{act} = \sum_j p^\text{act}_j C^\text{act}_j \in \mathbb{R}^{d_{	ext{rnn}}} \tag{21}
\]

\[
y^\text{act} = (q^\text{act})^T c^\text{val} \in \mathbb{R} \tag{22}
\]

In addition to real actions, we introduce a sentinel action to each turn which allows the attention
mechanism to ignore previous system actions. The score $y^{\text{act}}$ indicates the degree to which the value was expressed by the previous actions.

The final score $y$ is then a weighted sum between the two scores $y^{\text{utt}}$ and $y^{\text{act}}$, normalized by the sigmoid function $\sigma$.

$$y = \sigma(y^{\text{utt}} + wy^{\text{act}}) \in \mathbb{R}$$  \hspace{1cm} (23)

Here, the weight $w$ is a learned parameter.

3 Experiments

3.1 Dataset

The Dialogue Systems Technology Challenges (DSTC) provides a common framework for developing and evaluating dialogue systems and dialogue state trackers (Williams et al., 2013; Henderson et al., 2014a). Under this framework, dialogue semantics such as states and actions are based on a task ontology such as restaurant reservation. During each turn, the user informs the system of particular goals (e.g. inform(\text{food=french})), or requests for more information from the system (e.g. request(address)). For instance, \text{food} and \text{area} are examples of slots in the DSTC2 task, and \text{french} and \text{chinese} are example values within the \text{food} slot. We train and evaluate our model using DSTC2 as well as the Wizard of Oz (WoZ) restaurant reservation task (Wen et al., 2017), which also adheres to the DSTC framework and has the same ontology as DSTC2.

For DSTC2, it is standard to evaluate using the N-best list of the automatic speech recognition system (ASR) that is included with the dataset. Because of this, each turn in the DSTC2 dataset contains several noisy ASR outputs instead of a noise-free user utterance. The WoZ task does not provide ASR outputs, and we instead train and evaluate using the user utterance.

3.2 Metrics

We evaluate our model using turn-level request tracking accuracy as well as joint goal tracking accuracy. Our definition of GLAD in the previous sections describes how to obtain turn goals and requests. To compute the joint goal, we simply accumulate turn goals. In the event that the current turn goal specifies a slot that has been specified before, the new specification takes precedence. For example, suppose the user specifies a \text{food=french} restaurant during the current turn. If the joint goal has no existing \text{food} specifications, then we simply add \text{food=french} to the joint goal. Alternatively, if \text{food=thai} had been specified in a previous turn, we simply replace it with \text{food=french}.

3.3 Implementation Details

We use fixed, pretrained GloVe embeddings (Pennington et al., 2014) as well as character n-gram embeddings (Hashimoto et al., 2017). Each model is trained using ADAM (Kingma and Ba, 2015). For regularization, we apply dropout with 0.2 drop rate (Srivastava et al., 2014) to embeddings and the output of each local and global module. We use the development split for hyperparameter tuning and apply early stopping using the joint goal accuracy.

For the DSTC2 task, we train using transcripts of user utterances and evaluate using the noisy ASR transcriptions. During evaluation, we take the sum of the scores resulting from each ASR output as the output score of a particular slot-value. We then normalize this sum using a sigmoid function as shown in Equation (23). We also apply word dropout, in which the embeddings of a word is randomly set to zero with a probability of 0.3. This accounts for the poor quality of ASR outputs in DSTC2, which frequently miss words in the user utterance. We did not find word dropout to be helpful for the WoZ task, which does not contain noisy ASR outputs.

3.4 Comparison to Existing Methods

Table 1 shows the performance of GLAD compared to previous state-of-the-art models. The delexicalisation models, which replace slots and values in the utterance with generic tags, are from Henderson et al. (2014b) for DSTC2 and Wen et al. (2017) for WoZ. Semantic dictionaries map slot-value pairs to hand-engineered synonyms and phrases. The NBT (Mrkšić et al., 2017) applies CNN over word embeddings learned over a paraphrase database (Wieting et al., 2015) instead of delexicalised n-gram features.

On the WoZ dataset, we find that GLAD significantly improves upon previous state-of-the-art performance by 3.7% on joint goal tracking accuracy and 5.5% on turn-level request tracking accuracy. On the DSTC dataset, which evaluates using noisy ASR outputs instead of user utterances, GLAD improves upon previous state of the art per-
Table 1: Test accuracies on the DSTC2 and WoZ restaurant reservation datasets. The other models are: delexicalisation DSTC2 (Henderson et al., 2014b), delexicalisation WoZ (Wen et al., 2017), and NBT (Mrkšić et al., 2017). We run 10 models using random seeds with early stopping on the development set, and report the mean and standard deviation test accuracies for each dataset.

| Model                                      | DSTC2 Joint goal | DSTC2 Turn request | WoZ Joint goal | WoZ Turn request |
|--------------------------------------------|------------------|---------------------|----------------|------------------|
| Delexicalisation-Based Model               | 69.1%            | 95.7%               | 70.8%          | 87.1%            |
| Delex. Model + Semantic Dictionary         | 72.9%            | 95.7%               | 83.7%          | 87.6%            |
| Neural Belief Tracker (NBT) - DNN          | 72.6%            | 96.4%               | 84.4%          | 91.2%            |
| Neural Belief Tracker (NBT) - CNN          | 73.4%            | 96.5%               | 84.2%          | 91.6%            |
| GLAD                                       | 74.5± 0.2%       | 97.5 ± 0.1%         | 88.1± 0.4%     | 97.1± 0.2%       |

Table 2: Ablation study showing turn goal, joint goal, and turn request accuracies on the dev. split of the WoZ dataset. For “- self-attn”, we use mean-pooling instead of self-attention. For “- LSTM”, we use self-attention over word embeddings.

| Model          | Tn goal | Jnt goal | Tn request |
|----------------|---------|----------|------------|
| GLAD           | 93.7%   | 88.8%    | 97.3%      |
| - global       | 88.8%   | 73.4%    | 97.3%      |
| - local        | 93.1%   | 86.6%    | 95.1%      |
| - self-attn    | 91.6%   | 84.4%    | 97.1%      |
| - LSTM         | 88.7%   | 71.5%    | 93.2%      |

3.5 Ablation study

We perform ablation experiments on the development set to analyze the effectiveness of different components of GLAD. The results of these experiments are shown in Table 2. We also show turn goal accuracy in addition to joint goal accuracy and turn request accuracy for reference.

**Temporal order is important for state tracking.** We experiment with an embedding-matching variant of GLAD with self-attention but without LSTMs. The weaker performance by this model suggests that representations that capture temporal dependencies is helpful for understanding phrases for state tracking.

**Self-attention allows slot-specific, robust feature learning.** We observe a consistent drop in performance for models that use mean-pooling over the temporal dimension as opposed to self-attention (Equations (4) to (6)). This stems from the flexibility in the attention context computation afforded by the self-attention mechanism, which allows the model to focus on select words relevant to the slot-value pair under consideration. Figure 4 illustrates an example in which local self-attention modules focus on relevant parts of the utterance. The model attends to relevant phrases that n-gram and embedding matching techniques do not capture (e.g., “within 5 miles” for the “area” slot).

**Global-local sharing improves goal tracking.** We study the two extremes of sharing between the global module and the local module. The first uses only the local module and results in degradation in goal tracking but does not affect request tracking (e.g., $\beta_s = 1$). This is because the former is a joint prediction over several slot-values with few training examples, whereas the latter predicts a single slot that has the most training examples.

The second uses only the global module and underperforms in both goal tracking and request tracking (e.g., $\beta_s = 0$). This model is less expressive, as it lacks slot-specific specializations except for the final scoring modules.

Figure 5 shows the performance of GLAD and the two sharing variants across different numbers of occurrences in the training data. GLAD consistently outperforms both variants for rare slot-value pairs. For slot-value pairs with an abundance of training data, there is no significant performance difference between models as there is sufficient data to generalize.

3.6 Qualitative analysis

Table 3 shows example predictions by GLAD. In the first example, the user explicitly outlines requests and goals in a single utterance. In the second example, the model previously prompted the user for confirmation of two requests (e.g., for the restaurant’s address and phone number), and the user simply answers in the affirmative. In this
wait, you never gave me the information. find me a chinese restaurant within 5 miles.

Figure 4: Global and local self-attention scores on user utterances. Each row corresponds to the self-attention score for a particular slot. Slot-specific local self-attention modules emphasize relevant key words and phrases to that slot, whereas the global module attends to all relevant words.

Figure 5: F1 performance for each slot-value pair in the development split of the WoZ task, grouped by the number of training instances.

case, the model obtains the correct result by lever-aging the system actions in the previous turn. The last example demonstrates an error made by the model. Here, the user does not answer the system’s previous request for the choice of food and instead asks for what food is available. The model misinterprets the lack of response as the user not caring about the choice of food.

4 Related Work

Dialogue State Tracking. Traditional dialogue state trackers rely on a separate SLU component that serves as the initial stage in the dialogue agent pipeline. The downstream tracker then combines the semantics extracted by the SLU with previous dialogue context in order to estimate the current dialogue state (Thomson and Young, 2010; Wang and Lemon, 2013; Williams, 2014; Perez and Liu, 2017). Recent results in dialogue state tracking show that it is beneficial to jointly learn speech understanding and dialogue tracking (Henderson et al., 2014b; Zilka and Jurcicek, 2015; Wen et al., 2017). These approaches directly take as input the N-best list produced by the ASR system. By avoiding the accumulation of errors from the initial SLU component, these joint approaches typically achieved stronger performance on tasks such as DSTC2. One drawback to these approaches is that they rely on hand-crafted features and complex domain-specific lexicon (in addition to the ontology), and consequently are difficult to extend and scale to new domains. The recent Neural Belief Tracker (NBT) by Mrkšić et al. (2017) avoids reliance on hand-crafted features and lexicon by using representation learning. The NBT employs convolutional filters over word embeddings in lieu of previously-used hand-engineered features. Moreover, to outperform previous methods, the NBT uses pretrained embeddings tailored to retain semantic relationships by injecting semantic similarity constraints from the Paraphrase Database (Wieting et al., 2015; Ganitkevitch et al., 2013). On the one hand, these specialized embeddings are more difficult to obtain than word embeddings from language modeling. On the other hand, these embeddings are not specific to any dialogue domain and generalize to new domains.

Neural attention models in NLP. Attention mechanisms have led to improvements on a variety of natural language processing tasks. Bahdanau et al. (2015) propose attentional sequence to sequence models for neural machine translation. Luong et al. (2015) analyze various attention techniques and highlight the effectiveness of the simple, parameterless dot product attention. Similar models have also proven successful in tasks such as summarization (See et al., 2017; Paulus et al.,
Table 3: Example predictions by Global-Locally Self-Attentive Dialogue State Tracker on the development split of the WoZ restaurant reservation dataset. Model predicted slot-value pairs that are not in the ground truth (e.g. false positives) are prefaced with a “+” symbol. Ground truth slot-value pairs that are not predicted by the model (e.g. false negatives) are prefaced with a “-” symbol.

| System actions in previous turn | User utterance | Predicted turn belief state |
|--------------------------------|----------------|----------------------------|
| N/A                            | I would like Polynesian food in the South part of town. Please send me phone number and address. | request(phone) request(address) inform(food=polynesian) inform(area=south) |
| request(address) request(phone) | Yes please. | request(phone) request(address) |
| There is a moderately priced italian place called Pizza hut at cherry hilton. would you like the address and phone number? | | |
| request(food) request(price range) | I just want to eat at a cheap restaurant in the south part of town. What food types are available, can you also provide some phone numbers? | request(phone) inform(price range=cheap) inform(area=south) -inform(food=dontcare) +request(food) |

5 Conclusions

We introduced the Global-Locally Self-Attentive Dialogue State Tracker (GLAD), a new state-of-the-art model for dialogue state tracking. At the core of GLAD is the global-locally self-attention encoder, whose global modules allow parameter sharing between slots and local modules allow slot-specific feature learning. This allows GLAD to generalize on rare slot-value pairs with few training data. GLAD achieves state-of-the-art results of 88.1% goal accuracy and 97.1% request accuracy on the WoZ dialogue state tracking task, as well as 74.5% goal accuracy and 97.5% request accuracy on DSTC2.

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