A Joint and Domain-Adaptive Approach to Spoken Language Understanding

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Abstract

Spoken Language Understanding (SLU) is composed of two subtasks: intent detection (ID) and slot filling (SF). There are two lines of research on SLU. One jointly tackles these two subtasks to improve their prediction accuracy, and the other focuses on the domain-adaptation ability of one of the subtasks. In this paper, we attempt to bridge these two lines of research and propose a joint and domain adaptive approach to SLU. We formulate SLU as a constrained generation task and utilize a dynamic vocabulary based on domain-specific ontology. We conduct experiments on the ASMixed and MTOD datasets and achieve competitive performance with previous state-of-the-art joint models. Besides, results show that our joint model can be effectively adapted to a new domain.

1 Introduction

Spoken Language Understanding (SLU) is a critical component in spoken dialogue systems. It usually involves two subtasks: intent detection (ID) and slot filling (SF). ID aims to identify the intent of the user, while SF aims to extract the necessary information in the form of slots.

In recent years, there are two lines of research on SLU. One aims to improve the prediction accuracy of ID and SF. These models often learn ID and SF jointly by regarding ID as an utterance classification problem and SF as a sequence labeling problem. Following this Classify-Label framework, various joint models have been proposed (Liu and Lane, 2016; Zhang and Wang, 2016; Goo et al., 2018; Niu et al., 2019; Zhang et al., 2020b). These joint models can utilize the semantic correlation between intent and slot and hence result in higher prediction accuracy than separate models. Despite its success, the Classify-Label framework lacks domain adaptation ability. This is because the category label spaces of the source domains and target domains, which are made up of class indexes, are not necessarily equivalent.

The other line of research aims to improve models’ domain adaptation ability. These models only focus on one of the subtasks (either ID (Xia et al., 2018; Liu et al., 2019a; Zhang et al., 2020a) or SF (Bapna et al., 2017; Shah et al., 2019; Liu et al., 2020)). However, the separate approach has been shown to be inferior to the joint approach in terms of prediction accuracy as it fails to utilize the semantic correlation between slot and intent (Zhang and Wang, 2016; Goo et al., 2018; Zhang et al., 2020b).

In this paper, we attempt to bridge these two lines of research and propose a joint and domain-adaptive approach to SLU. Different from previous joint models which follows the Classify-Label framework, we approach SLU from a relatively new perspective by formulating SLU as a text-to-text (T2T) task. As shown in Figure 1, we define a general format of the output sequence as: 

\[ \text{\langle intent\rangle} [T] \langle slot \text{name}\rangle [:] \langle slot \text{value}\rangle [T] \langle slot \text{name}\rangle [:] \langle slot \text{value}\rangle \ldots \text{, where} [T] \text{and} [:] \text{are separators. Here all the} \text{\langle intent\rangle,} \text{\langle slot \text{name}\rangle} \text{and} \text{\langle slot \text{value}\rangle} \text{are expressed in natural language.} \]

For this T2T setting, a natural model choice is the popular Seq2Seq framework (Cho et al., 2014; Sutskever et al., 2014) with copy mechanism (See et al., 2017) to tackle this task. Since this model sets no constraints to the output, we name it as Unconstrained-T2T (UT2T). It depends on the model itself to infer the intent and slots using any words in the vocabulary, hence the output may not exactly match domain definition, even if the semantic may be correct.

To this end, we further propose the Constrained-T2T (CT2T) that utilizes different vocabularies for different segments of the output sequence. It also supports domain-specified intent/slot definitions. At the first decoding step, it generates words us-
Please find the movie Troop Zero

| ID | B-object type | B-object name | I-object name |
|----|---------------|---------------|---------------|
| O  | O             | O             | O             |

search creative work

ID search creative work [T] object type [:] movie [T] object name [:] Troop Zero

Figure 1: Traditional joint approach regards ID as a classification task and SF as a sequence labeling task, making domain adaptation impossible. By contrast, T2T approach regards SLU as a generation task, where all ID/SF labels are expressed in natural language in the output sequence.

ing the intent vocabulary. To decode the following slot name-value pairs, it learns how to alternatively select tokens from the slot vocabulary and the input utterance. For domain adaptation, we feed the domain-specified intent/slot names into the model, along with the input utterance. Even if some intents/slots are not exactly seen in the training domains, our model can utilize the semantic information their names convey to generate the correct results. For example, if our model has seen the intent cancel alarm in the Alarm domain, then it may well be able to generate cancel reminder in the Reminder domain.

We conduct experiments on two major multi-domain SLU datasets, ASMixed and MTOD. Our CT2T achieves sentence-level accuracy of 84.87% and 91.24% on the two datasets, respectively, on par with the best joint model following the Classify-Label framework. Besides, both few-shot and zero-shot experiments show that it can be effectively adapted to a new domain.

2 Related Work

Joint Learning. In recent years, the Classify-Label framework has been the default design for joint ID and SF. It regards ID as an utterance classification task and SF as a sequence labeling task. Following this framework, various joint models have been proposed (Liu and Lane, 2016; Zhang and Wang, 2016; Goo et al., 2018; Niu et al., 2019; Qin et al., 2019; Liu et al., 2019b; Zhang et al., 2020b; Wu et al., 2020). Since these joint models can utilize the semantic correlation between intent and slot, they often result in higher prediction accuracy than separate models.

There are few joint models investigating the problem of domain adaptation. Most of these models conduct experiments on single domain datasets such as ATIS (Hemphill et al., 1990) and Snips (Coucke et al., 2018). There have also been joint models that focused on multi-domain SLU (Liu and Lane, 2017; Kim et al., 2017), yet these models are not domain-adaptive. Although Qin et al. (2020) conduct domain adaptation experiments, they actually train a new model using data of both the source and target domains when adapting to the target domain\(^1\).

**Domain Adaptation.** There are also SLU models focusing on domain adaptation. For example, Bapna et al. (2017); Shah et al. (2019); Liu et al. (2020) utilize slot descriptions to achieve zero-shot SF. In a sense, their methods are close to our work, as they often use tokenized slot names in place of slot description in practice. However, they need to perform multiple times of labeling for each slot (Bapna et al., 2017; Shah et al., 2019) or require a two-steps pipeline to decide the exact slot types (Liu et al., 2020), while our model decodes the whole output sequence once and obtains all slot name-value pairs. Besides, there are also works that investigate zero/few-shot ID (Xia et al., 2018; Liu et al., 2019a; Lin and Xu, 2019; Yan et al., 2020; Zhang et al., 2020).

In general, all these works are restricted to either ID or SF, hence cannot enjoy the benefits brought by joint learning.

**Seq2Seq for SLU.** Seq2Seq learning was first proposed by Cho et al. (2014); Sutskever et al. (2014) for Machine Translation. There are previous works that apply the Seq2Seq framework to SLU (Liu and Lane, 2016; Zhu and Yu, 2017). However, they still follow the Classify-Label framework, meaning that the output of their decoder is a label sequence following the BIO format, rather than natural language. Therefore, they still suffer from the two limitations we mentioned before.

For SLU, the slot values are all from the source utterance, hence we add the copy mechanism (Vinyals et al., 2015; See et al., 2017) into our model. In this respect, our UT2T is close to Zhao and Feng (2018), who first applied copy mechanism for slot value prediction. However, their model only predicts slot values but not corresponding slot names, which limits its practical applications. By contrast, our model can predict intent, slot names and slot values in a single sequence. Our work is notably different from Wu et al. (2019), which employ Seq2Seq for the task of dialogue

\(^1\)Please refer to Section 4.5.4 of their paper
Figure 2: UT2T is Seq2Seq with copy mechanism without any constraints. It depends on the model itself to infer the intent and slots using any words in the vocabulary.

state tracking (DST). They decode slot value \( J \) times independently for all the possible slot names, where \( J \) is the number of possible slots. Besides, their model does not involve intent detection.

3 Models

3.1 Task Formalization

Given an input utterance \( \mathcal{X} = x_1, x_2, \ldots, x_n \), where \( n \) denotes the length of the sequence, SF needs to find every slot value in \( \mathcal{X} \), and then assign a slot label to it. ID aims to decide the intent type of \( \mathcal{X} \).

In this work, we tackle both ID and SF jointly and regard them as a text-to-text task. We define a general format of the output sequence as:

\[
\text{<intent>[T]<slot name>[;]<slot value>[T]}
\]

\[
\text{<slot name>[;]<slot value>...}
\]

where \([T]\) and \([;]\) are separators, and all the \(<\text{intent}>\), \(<\text{slot name}>\) and \(<\text{slot value}>\) are expressed in natural language.

From the tagging-style annotated SLU dataset, this output sequence is constructed based on the following rules:

1. The intent type of \( \mathcal{X} \) is simply put at the beginning of the output sequence, followed by a series of slot name-value pairs.

2. The slot values are extracted from the BIO-tagged sequence. Take Figure 1 as an example, since \( \text{Troop} \) is tagged \text{B-object name} and \( \text{Zero} \) is tagged \text{I-object name}, we can hence extract slot value \( \text{Troop Zero} \) and specify its slot name as \text{object name}.

3. The order of different slot name-value pairs in the output sequence is the same as that of their occurrence in the input utterance. Take Figure 1 as an example, \text{object type [:]} \text{movie} should be put before \text{object name [:]} \text{Troop Zero} in the output sequence, as \text{movie} occurs before \text{Troop Zero} in the input utterance.

3.2 UT2T

We first explore using a standard sequence-to-sequence generation with copy mechanism (See et al., 2017) to tackle this problem. As shown in Figure 2, we first encode the input utterance \( \mathcal{X} = x_1, x_2, \ldots, x_n \) into \( H = h_1, h_2, \ldots, h_n \). In this work, we experiment with both non-pretrained LSTM encoder and pretrained RoBERTa (Liu et al., 2019c) encoder.

For the decoder, we use LSTM and update its hidden state \( s_t \) at time step \( t \):

\[
s_t = \text{LSTM}(\vec{v}_t, s_{t-1})
\]

where \( \vec{v}_t \) is the embedding of the previous word. While training, this is the previous word of the ground truth; at test time it is the previous word emitted by the decoder.

The attention distribution is calculated as in (Luong et al., 2015):

\[
\alpha_t^i = \text{softmax}(s_t W_g h_i)
\]

where \( W_g \) are model parameters.

Then, the attention weights \( \alpha_t^i \) are used to produce a weighted sum of the encoder hidden states, known as the context vector \( c_t \), which is then concatenated with the decoder state \( s_t \) to produce the vocabulary distribution \( P_{\text{vocab}} \):

\[
c_t = \sum_i \alpha_t^i h_i
\]

\[
m_t = \tanh \left(W_a [c_t; s_t] + b_a \right)
\]

\[
P_{\text{vocab}} = \text{softmax} (m_t)
\]

where \( W_a, b_a \) are model parameters.

Note that the slot values are not always in the vocabulary. To solve this out-of-vocabulary (OOV) problem, we further employ the copy mechanism (See et al., 2017) to copy slot values from the input utterance. The attention distribution \( \alpha_t^i \) and the vocabulary distribution \( P_{\text{vocab}} \) are then weighted and summed to obtain the final word distribution:

\[
p_{\text{gen}} = \sigma \left(w_t^T m_t + w_s^T s_t + w_e^T \vec{v}_t + b_{\text{gen}} \right)
\]
3.3 CT2T

UT2T depends on the model itself to infer the intent and slots using any words in the vocabulary, hence the output may not exactly match domain definition. Take the example of Figure 1, the model may generate find creative work, rather than search create work, failing to match the definition of domain Reminder. To solve this limitation, we further propose the CT2T.

As mentioned above, the output format is defined in Equation (1) where <intent> and <slot name> are defined in a domain-specific ontology, and <slot value> is a span of the input sequence. It is a sequence starting with the intent, followed by a series of slot name-value pairs. We can hence exploit this pattern and construct a small, dynamic vocabulary for different segments of the output sequence.

As shown in Figure 3, we first encode the input utterance \( \mathcal{X} = x_1, x_2, ..., x_n \) into \( \mathcal{H} = h_1, h_2, ..., h_n \) with our encoder. In this work, we experiment with both LSTM and pretrained RoBERTa encoders.

At the first decoding step, we feed the intent vocabulary \( \mathcal{I} = \text{intent}_1, \text{intent}_2, ..., \text{intent}_{N_i} \) to the model, where \( N_i \) is the number of domain-specific intents. Each intent \( \text{intent}_i \) is composed of \( T \) words \( w_{i1}, w_{i2}, ..., w_{iT} \), where \( T \) may vary among different intents. We encode \( \text{intent}_i \) into a fixed-length vector via max-pooling:

\[
vec^{\text{intent}}_i = \text{Pooling}(\text{Encoder}(w_{i1}, w_{i2}, ..., w_{iT})) \tag{7}
\]

After obtaining intent vectors \( vec^{\text{intent}}_i \), we compute the attention scores between the current hidden state \( s_1 \) and \( vec^{\text{intent}}_i \):

\[
\delta_i = \text{softmax} (s_1 W_i vec^{\text{intent}}_i) \tag{8}
\]

where \( W_i \) is model parameter. The intent with the highest attention weight \( \delta_i \) is outputted. Note that the multi-words intent is outputted in one decoding step.

To decode the following slot name-value pairs, we choose from the slot vocabulary and words from the input utterance. The slot vocabulary \( \mathcal{S} = \text{slot}_1, \text{slot}_2, ..., \text{slot}_{N_s} \) contains \( N_s \) possible slots. Each slot \( \text{slot}_i \) is composed of \( T \) words \( w_{i1}, w_{i2}, ..., w_{iT} \), where \( T \) may vary among different slots. We encode each slot \( \text{slot}_i \) into a fixed-length vector:

\[
vec^{\text{slot}}_i = \text{Pooling}(\text{Encoder}(w_{i1}, w_{i2}, ..., w_{iT})) \tag{9}
\]
Then we calculate the attention scores $\gamma^t_i$ between the current hidden state $s_t$ and slot vector $vec^{slot}_t$, and the attention score $\alpha^t_i$ between $s_t$ and the input hidden state $h_i$:

$$\gamma^t_i = \text{softmax} \left( s_t W_s vec^{slot}_t \right)$$
$$\alpha^t_i = \text{softmax} \left( s_t W_h h_i \right)$$

(10)

where $W_s, W_h$ are model parameters.

This two distributions $\gamma^t_i$ and $\alpha^t_i$ are then weighted and summed to obtain the final word distribution.

$$p_{\text{slot}} = \sigma \left( w_a^T m_t + w_s^T s_t + w_c^T c_t + b_{\text{slot}} \right)$$

(11)

$$P(w) = p_{\text{slot}} \sum_{i : w_i = w} \gamma^t_i + (1 - p_{\text{slot}}) \sum_{i : w_i = w} \alpha^t_i$$

(12)

where $w_a, w_s, w_c$ and $b_{\text{slot}}$ are model parameters. $m_t$ is calculated as in Equation 4. The $p_{\text{slot}}$ can be seen as a soft switch to choose between slot vocabulary (for $<\text{slot name}>$) and from the input utterance (for $<\text{slot value}>$).

Note that the multi-words slot name is outputted as a whole, while slot value is outputted one word at a time.

Unlike traditional joint models, CT2T can be transferred to a new domain. Even though there may exist intents/slots that are not exactly seen in the training domains, it can utilize the semantic information their names convey to generate the correct ones. CT2T also improves on previous separate, domain-adaptive models. This is because CT2T is a joint model, the information of one task can be utilized in the other task to promote each other.

4 Experiments

4.1 Datasets

Following Qin et al. (2020), we conducted experiments on the ASMixed and MTOD datasets. The statistics of the two datasets are shown in Table 1.

ASMixed - The ASMixed (Qin et al., 2020) dataset was created by mixing the ATIS (Hemphill et al., 1990) and Snips (Coucke et al., 2018) datasets. The ATIS (Hemphill et al., 1990) dataset has long been used as a benchmark in SLU. There are 4478 utterances in the training set, 500 in the valid set, and 893 in the test set, with a total of 120 distinct slot labels and 21 different intent types. The Snips dataset was created by snips.ai (Coucke et al., 2018). It is in the domain of personal assistant commands. There are 72 slot labels and 7 intent types.

MTOD - The MTOD (Schuster et al., 2018) dataset contains three domains including alarm, reminder, and weather. We follow the same format and partition as in (Schuster et al., 2018; Qin et al., 2020). There are 30521, 4181, and 8621 utterances in the training, validation, and test set, respectively. There are in total 12 intent types and 11 slot types.

4.2 Evaluation Metrics

We extract the intent and slots from the output sequence using separator $|T|$ and adopt three mainstream evaluation metrics:

We evaluate the system’s performance on SF using the F1 score, which is defined as the harmonic average of precision and recall. The metric for ID is classification accuracy. Besides, following previous work of Goo et al. (2018); Niu et al. (2019); Qin et al. (2020), we also report the sentence-level accuracy, which considers both SF and ID performance. A sentence is counted as correct if all its slots and intent are correctly predicted.

4.3 Implementation Details

For both the pretrained and non-pretrained model, we set the batch size to 128. Dropout (Hinton et al., 2012) layers are applied on both input and output vectors during training for regularization. We use greedy decoding for the decoder.

For the non-pretrained model, we use LSTM as the encoder. The dimensions of LSTM hidden state and embeddings are both set to 256. We use Adam for the training process to minimize the cross-entropy loss, with learning rate $= 10^{-3}$, $\beta_1 = 0.9$, $\beta_2 = 0.98$, and $\epsilon = 10^{-9}$.

For the pretrained model, we employ the pre-trained RoBERTa-base model as our encoder. The dimensions are set to 768. We adopt AdamW (Loshchilov and Hutter, 2018) as our optimizer.

Table 1: Statistics of ASMixed and MTOD datasets.
Since the encoder makes use of a pretrained model, whereas the decoder needs to be trained from scratch, we use different learning rate schemes for the encoder and the decoder. We set the peak learning rate and warmup proportion to $4e^{-5}$ and 0.2 for the encoder and $1e^{-4}$ and 0.1 for the decoder, respectively. The token embedding matrix of the decoder is shared with that of RoBERTa.

We use teacher forcing for model training where the ground truth instead of the predicted ones is used. During training, we found that the MTOD dataset is more likely to overfit. We train our model for 50 and 200 epochs, and the dropout rates are set to 0.6 and 0.5 for the ASMixed and MTOD datasets, respectively. For all the experiments, we select the model which reports the highest sentence-level accuracy on the validation set and evaluate it on the test set.

### 4.4 Systems for Comparison

We compared our model against the following multi-domain SLU baselines:\footnote{All the baseline results are taken from Qin et al. (2020)}

- **Shared-LSTM** (Hakkani-Tür et al., 2016) used a single shared LSTM for both ID and SF for all the domains.
- **Separated-LSTM** (Hakkani-Tür et al., 2016) performed ID and SF for each domain separately.
- **Multi-Domain Adv** (Liu and Lane, 2017) proposed an adversarial training model to learn common features that can be shared across multi-domains.
- **One-Net** (Kim et al., 2017) jointly performed domain, intent, and slot prediction, aiming to alleviate error propagation and lack of information sharing.
- **Locale-agnostic-Universal** (Lee et al., 2019) proposed a locale-agnostic universal domain classification model that learns a joint representation of an utterance over locales with different sets of domains.

**Domain-Aware** (Qin et al., 2020) proposed to improve the parameterization of multi-domain learning by using domain-specific and task-specific model parameters to improve knowledge learning and transfer.

### 5 Results

#### 5.1 Overall Performance

The overall performance on the ASMixed and MTOD datasets are demonstrated in Table 2\footnote{When adopting RoBERTa as encoder, \textit{CT2T} achieves sentence-level accuracy of 87.32\% and 92.19\% on the ASMixed and MTOD and datasets, respectively. However, for a fair comparison, we do not list the results in Table 2.}.

| Model | ASMixed | MTOD |
|-------|---------|------|
|       | ID      | SF   | Sent. | ID   | SF  | Sent. |
| Shared-LSTM (Hakkani-Tür et al., 2016) | 94.41 | 92.55 | 76.71 | 98.70 | 94.87 | 88.71 |
| Separated-LSTM (Hakkani-Tür et al., 2016) | 94.79 | 92.94 | 79.53 | 99.01 | 94.89 | 89.73 |
| Multi-Domain adv (Liu and Lane, 2017) | 94.79 | 92.94 | 79.47 | 99.01 | 94.89 | 88.82 |
| One-Net (Kim et al., 2017) | 93.72 | 93.38 | 78.28 | 98.56 | 95.25 | 89.36 |
| Local-agnostic-Universal (Lee et al., 2019) | 96.48 | 92.10 | 79.35 | 99.12 | 94.16 | 88.82 |
| Domain-Aware † (Qin et al., 2020) | 97.30 | 94.30 | 84.81 | 99.20 | 95.69 | 91.27 |
| UT2T | 96.74 | 93.37 | 83.55 | 99.11 | 95.48 | 90.99 |
| CT2T | 97.49 | 94.34 | 84.87 | 99.21 | 95.54 | 91.24 |

Table 2: Main results on the ASMixed and MTOD datasets (%). Best sentence-level accuracy results are boldfaced. † means using external knowledge.
and utilizes it as external knowledge when encoding input utterance, while our \textit{CT2T} relies on no additional information beyond the dataset.

Compared with traditional joint models, the reason why \textit{CT2T} gives such competitive performance is that it makes better use of the semantic information of each individual word in intent/slot, rather than regarding intent/slot as class index.

5.2 Domain Adaptation

In this section we test our model’s domain adaptation ability. For the \textit{Transfer} setting, each model is trained on two domains of the MTOD dataset, and a held-out domain is reserved. Then we fine-tune our model on the held-out domain with x% training data, and evaluate its performance on the held-out domain. For the \textit{From-Scratch} setting, we omit the training process and directly fine-tune and test the model on the held-out domain\(^5\). The results are shown in Figure 4.

We first note that models following the \textit{Classify-Label} framework cannot achieve domain adaptation on any of these domains. This is because the category label spaces of the training domains and the held-out domain are not equivalent.

By formulating SLU as a text-to-text task, \textit{UT2T} demonstrates certain domain adaptation ability. We can see that the \textit{Transfer} curves are higher than the \textit{From Scratch} curves on all three domains, showing the benefits brought by transfer learning. However, we also note that the absolute value is low, especially for domain \textit{Reminder} and \textit{Weather}. Even with 50% training data, its sentence-level accuracy on the two domains are lower than 20%. Detailed analysis shows that this is because \textit{UT2T} does not support user-specified ontology. For example, it can never generate the slot name \texttt{Reminder todo}, when trained on the \textit{Alarm} and \textit{Weather} domains and transferred to the \textit{Reminder} domain, since the word \texttt{todo} is in neither the model vocabulary nor the input utterance.

On the other hand, our \textit{CT2T} gives much more satisfactory performance. Not only its \textit{Transfer} results are higher than the \textit{From Scratch} results on all three domains, but also it achieves much higher absolute value than \textit{UT2T}. For example, it achieves 38.31% sentence-level accuracy after fine-tuning using only 1% of \texttt{reminder} domain data, outperforming the From-Scratch method by as large as 31.99%. Besides, it also outperforms the \textit{Transfer} result of \textit{UT2T} by more than 30%.

5.3 Zero-Shot Analysis

We further give detailed analysis on \textit{CT2T}’s zero-shot ability. We select the \texttt{reminder} domain and report performance on each individual intent/slot. The model is first trained on the \texttt{alarm} and \texttt{weather} domains and then tested on the \texttt{reminder} domain.

Figure 4: Domain adaptation results. \textit{Reminder}, \textit{Alarm} and \textit{Weather} stand for the three domains in the MTOD dataset. We report sentence-level accuracy that considers both ID and SF. Note that the comparison is not only between Transfer and From-Scratch, but also between \textit{UT2T} and \textit{CT2T}.
Figure 5: Detailed domain adaptation analysis on the reminder domain. The first and last three rows stand for intents and slots, respectively. The gray and black bars indicate zero-shot and few-shot (with 1% training data) results.

without further model parameter update. The results are shown in Figure 5.

As we can see, CT2T achieves striking accuracy in terms of zero-shot ID on the reminder domain. The three intents achieve more than 90% accuracy, without any training instance of the reminder domain. The reason is that although intents such as cancel reminder are not seen during training, there are similar intents such as cancel alarm in the alarm domain. Since CT2T regards intents as natural language, the semantic meaning of the word cancel is successfully transferred to a new domain, and help our model to generate the correct intent. Note that for the traditional joint model, where the intents are regarded as class indexes, this kind of transfer cannot be realized.

Based on the slots already learned, our model is able to directly track those slots that are present in a new domain. For example, CT2T achieves high performance on the date time slot on domain reminder, as date time also appears in the weather domain. On the other hand, the zero-shot results on the reminder noun and reminder todo slots are pool, as the model has never seen similar semantics in the training domains. However, with as little as 1% training data, the results on these two slots are dramatically improved. Another way to solve this problem is to enlarge slot semantics coverage in training data by adding more domains. We leave this to our future work.

5.4 Case Study

To better understand the model performance, we provide a case study in Figure 6.

Our first observation is that the format of the output sequence is well-learned. After the model fully converged, we see no cases that break the format rule specified in Equation 1, which makes T2T approach to SLU possible.

The second observation is that the pretrained language model is a great help on general semantics. Take the second case in Figure 6, the intent of the utterance should be set alarm, yet the model wrongly predicts it as cancel alarm. The reason is that the semantic meaning of the word reset is not well trained. When adopting RoEBRTa as the encoder, the model is able to fix this type of error.

We also observe a common error rising from the boundary of slot values. As shown in the third case, the value for slot location should be big island of hawaii, yet our model simply predicts it as hawaii. Even with RoEBRTa as our encoder, this error is still not fixed. Strictly speaking, this kind of error is not caused by poor language understanding ability, but the existence of nested entities. There are some works (Zheng et al., 2019) that aim to solve this problem, but it is beyond the scope of this paper.

6 Conclusions

In this paper, we propose a joint and domain adaptive SLU model based on T2T setting. We first explore the unconstrained generation approach and show that it is workable for SLU. Then, we propose the CT2T where different vocabularies are constructed for different segments of the output sequence. Our CT2T achieves very competitive performance on two SLU datasets. Further experiments demonstrate that the model trained on the source domains can be effectively adapted to a new domain.
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