A Co-Interactive Transformer for Joint Slot Filling and Intent Detection

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Abstract

Intent detection and slot filling are two main tasks for building a spoken language understanding (SLU) system. The two tasks are closely related and the information of one task can be utilized in the other task. Previous studies either model the two tasks separately or only consider the single information flow from intent to slot. None of the prior approaches model the bidirectional connection between the two tasks simultaneously. In this paper, we propose a Co-Interactive Transformer to consider the cross-impact between the two tasks. Instead of adopting the self-attention mechanism in vanilla Transformer, we propose a co-interactive module to consider the cross-impact by building a bidirectional connection between the two related tasks. In addition, the proposed co-interactive module can be stacked to incrementally enhance each other with mutual features. The experimental results on two public datasets (SNIPS and ATIS) show that our model achieves the state-of-the-art performance with considerable improvements (+3.4% and +0.9% on overall acc). Extensive experiments empirically verify that our model successfully captures the mutual interaction knowledge.

1 Introduction

Spoken language understanding (SLU) typically consists of two typical subtasks including intent detection and slot filling, which is a critical component in task-oriented dialogue systems (Tur and De Mori, 2011). For example, given “watch action movie”, intent detection can be seen an classification task to identify an overall intent class label (i.e., WatchMovie) and slot filling can be treated as a sequence labeling task to produce a slot label sequence (i.e., O, B-movie-type, I-movie-type). Intuitively, the two tasks are closely tied. For example, if the intent of an utterance is WatchMovie, it is more likely to include the movie_type related slots rather than that of music_type. Similarly, if an utterance is predicted as movie_type related slots, the intent of the whole utterance is more likely to be WatchMovie. Hence, it is important to take the cross-impact between the two tasks into account.

Considering such close relationship, dominant SLU systems in the literature (Liu and Lane, 2016; Zhang and Wang, 2016; Goo et al., 2018; Li et al., 2018; Qin et al., 2019) proposed joint model to consider the correlation between the two tasks. Existing joint models can be classified into two main categories. As shown in Figure 1(a), the first strand of work (Liu and Lane, 2016; Zhang and Wang, 2016) adopted a multi-task framework with a shared encoder to solve the two tasks jointly. While these models outperform the pipeline models via mutual enhancement, they just model the relationship implicitly by sharing parameters. In addition, the shared representation is almost a block box that makes it hard to analyze the effect of the mutual interaction. This limits the interpretability. As shown in Figure 1(b), the second strand of work (Goo et al., 2018; Li et al., 2018; Qin et al., 2019) explicitly applied the intent information to guide the slot filling task and achieve the state-of-the-art performance. However, they only considered the single information flow from intent to slot, ignoring to explicitly apply slot information to guide the intent detection. This results in failing to effectively establishing a bidirectional connection...
and taking advantage of the cross-impact between intent detection and slot filling, which is shown in Figure 1(c).

We consider addressing the limitation of existing works by proposing a Co-Interactive Transformer for joint slot filling and intent detection. Different with the vanilla Transformer (Vaswani et al., 2017), the core component in our framework is a proposed co-interactive module to model the relation and interaction between the two tasks, aiming to consider the cross-impact of the two tasks and enhance the two tasks in a mutual way. Specifically, in each co-interactive module, we first apply label attention mechanism (Cui and Zhang, 2019) over intent and slot label to capture the initial explicit intent and slot representations, which extracts the intent and slot semantic information. Second, the explicit intent and slot representations are fed into a co-interactive attention layer to make mutual interaction. In particular, the explicit intent representations are treated as queries and slot representations are considered as keys as well as values to obtain the slot-aware intent representations. Meanwhile, the explicit slot representations are used as queries and intent representations are treated as keys as well as values to get the intent-aware slot representations. Based on this operations, the bidirectional connection can be established. The underlying intuition behind is that slot and intent can be able to attend on the corresponding mutual information with the co-interactive attention mechanism. In addition, the co-interactive module can be stacked to form a hierarchy that enables multi-step interactions between the two tasks, which achieves incrementally capture mutual knowledge to enrich each other. More importantly, the knowledge transfer process can be controlled by whether considering one direction of information attention flow (intent → slot and slot → intent), which leads to more interpretable.

The experimental results on two benchmarks SNIPS (Coucke et al., 2018) and ATIS (Goo et al., 2018) show that our framework achieves significant and consistent improvement compared to all baselines. Besides, on overall acc, our method outperforms the current state-of-the-art method by 3.4% and 0.9% on SNIPS and ATIS, respectively. In particular, we incorporate the pre-trained model (Devlin et al., 2018, BERT) in our framework, which can achieve a new state-of-the-art performance. To the best of our knowledge, we are the first work to model the cross-impact between slot filling and intent detection simultaneously in an unified framework.

For reproducibility, our code for this paper is publicly available at [https://github.com/kangbrilliant/DCA-Net](https://github.com/kangbrilliant/DCA-Net).

2 Approach

In this section, we describe the proposed framework. Vanilla Transformer encoder is mainly composed of self-attention and feedforward network (FFN) layer, which are the main components we extend in our co-interactive Transformer. As shown in Figure 2, our framework mainly consists of three components including: a shared encoder (2.1), a co-interactive module (2.2) that explicitly establishes bidirectional connection between the two tasks and two separate decoders (2.3) for intent detection and slot filling.

2.1 Shared Encoder

We use BiLSTM (Hochreiter and Schmidhuber, 1997) as the shared encoder, which aims to leverage the advantages of temporal features within word orders and contextual information. BiLSTM consists of two LSTM layers. For the input sequence \( \{x_1, x_2, \ldots, x_n\} \) \( n \) is the number of tokens in the input.
Figure 2: The illustration of the co-interactive transformer.

utterance), BiLSTM reads it forwardly from $x_1$ to $x_n$ and backwardly from $x_n$ to $x_1$ to produce a series of context-sensitive hidden states $H = \{h_1, h_2, \ldots, h_n\}$ by repeatedly applying the recurrence $h_i = \text{BiLSTM}(\phi_{\text{emb}}(x_i), h_{i-1})$, where $\phi_{\text{emb}}(\cdot)$ represents the embedding function.

2.2 Co-Interactive Module

The Co-Interactive module is the core component of our framework to build the bidirectional connection between intent detection and slot filling. For simplicity, we describe one layer of the co-interactive module and it can be stacked with multi-layers interaction to gradually capture mutual interaction knowledge.

In vanilla Transformer, each sublayer consists of a self-attention and FFN layer. In contrast, in our co-interactive module, we first apply intent and slot label attention layer to obtain the explicit intent and slot representation. Then, we adopt a co-interactive attention layer instead of self-attention to explicitly model the mutual interaction between the two tasks. Finally, we extend the basic feed-forward network for further fusing intent and slot information in an implicit method.

2.2.1 Intent and Slot Label Attention Layer

Inspired by Cui and Zhang, 2019) that successfully captures label representations, we perform label attention over intent and slot label to get the explicit intent representation and slot representation. Then, they are fed into co-interactive attention layer to make a mutual interaction directly. In particular, we use the parameters of the fully-connected slot filling decoder layer and intent detection decoder layer as slot embedding matrix $W_S \in \mathbb{R}^{d \times |S_{\text{label}}|}$ and intent embedding matrix $W_I \in \mathbb{R}^{d \times |I_{\text{label}}|}$ ($d$ represents the hidden dimension; $|S_{\text{label}}|$ and $|I_{\text{label}}|$ represents the number of slot and intent label, respectively), which can be regarded as the distribution of labels in a certain sense.

**Intent Representations**  In practice, we use $H \in \mathbb{R}^{n \times d}$ as the query, $W_I \in \mathbb{R}^{d \times |I_{\text{label}}|}$ as the key and value to obtain intent representations $H_I$ with intent label attention:

$$A = \text{softmax}(HW_I), \quad (1)$$

$$H_I = H + AW_I. \quad (2)$$

**Slot Representations**  Similarly, we regard $H \in \mathbb{R}^{n \times d}$ as the query, $W_S \in \mathbb{R}^{d \times |S_{\text{label}}|}$ as the key and value, and then obtain the slot representations $H_S$:

$$A = \text{softmax}(HW_S), \quad (3)$$

$$H_S = H + AW_S. \quad (4)$$

$H_I \in \mathbb{R}^{n \times d}$ and $H_S \in \mathbb{R}^{n \times d}$ are the obtained explicit intent representation and slot representation, which capture the intent and slot semantic information, respectively.
2.2.2 Co-Interactive Attention Layer

$H_S$ and $H_I$ are used in next co-interactive attention layer to model mutual interaction between the two tasks. This makes the slot representation updated with the guidance of associated intent and intent representations updated with the guidance of associated slot, achieving a bidirectional connection with the two tasks.

**Intent-Aware Slot Representation** Same with the vanilla Transformer, we map the matrix $H_S$ and $H_I$ to queries ($Q_S$, $Q_I$), keys ($K_S$, $K_I$) and values ($V_S$, $V_I$) matrices by using different linear projections. To obtain the slot representations to incorporate the corresponding intent information, it is necessary to align slot with its closely related intent. We treat $Q_S$ as queries, $K_I$ as keys and $V_I$ as values. The output is a weighted sum of values:

$$C_S = \text{softmax} \left( \frac{Q_S K_I^\top}{\sqrt{d_k}} \right) V_I,$$

$$H'_S = \text{LN} \left( H_S + C_S \right),$$

where LN represents the layer normalization function (Ba et al., 2016).

**Slot-Aware Intent Representation** Similarly, We treat $Q_I$ as queries, $K_S$ as keys and $V_S$ as values to obtain intent representations:

$$C_I = \text{softmax} \left( \frac{Q_I K_S^\top}{\sqrt{d_k}} \right) V_S,$$

$$H'_I = \text{LN} \left( H_I + C_I \right).$$

$H'_S \in \mathbb{R}^{n \times d}$ and $H'_I \in \mathbb{R}^{n \times d}$ can be considered as leveraging the corresponding slot and intent information, respectively.

2.2.3 Feed-forward Network Layer

In this section, we extend feed-forward network layer to implicitly further fuse intent and slot information. We first concatenate $H'_I$ and $H'_S$ to combine the slot and intent information.

$$H_{IS} = H'_I \oplus H'_S,$$

where $H_{IS} = (h^1_{IS}, h^2_{IS}, \ldots, h^n_{IS})$ and $\oplus$ is concatenation operation.

Then, we follow (Zhang and Wang, 2016) to use word features for each token and the $t$ timestep is formatted as:

$$h^t_{(f,t)} = h^{t-1}_{IS} \oplus h^t_{IS} \oplus h^{t+1}_{IS},$$

where $H_{(f,t)} = (h^1_{(f,t)}, h^2_{(f,t)}, \ldots, h^L_{(f,t)})$.

Finally, the FFN layer further fuses the intent and slot information:

$$\text{FFN}(H_{(f,t)}) = \max(0, H_{(f,t)} W_1 + b_1) W_2 + b_2,$$

$$\hat{H}_I = \text{LN}(H'_I + \text{FFN}(H_{(f,t)})),$$

$$\hat{H}_S = \text{LN}(H'_S + \text{FFN}(H_{(f,t)})),$$

where $\hat{H}_I \in \mathbb{R}^{n \times d}$ and $\hat{H}_S \in \mathbb{R}^{n \times d}$ is the obtained updated intent and slot information that aligns the corresponding slot and intent features, respectively.

2.3 Decoder for Slot Filling and Intent Detection

In order to conduct sufficient interaction between the two tasks, we apply a stacked co-interactive attention network with multiple layers. After stacking $L$ layer, we obtain a final updated slot and intent representations $\hat{H}_I^{(L)} = (h^{(L)}_{(1,1)}, h^{(L)}_{(1,2)}, \ldots, h^{(L)}_{(1,n)}), \hat{H}_S^{(L)} = (h^{(L)}_{(S,1)}, h^{(L)}_{(S,2)}, \ldots, h^{(L)}_{(S,n)})$. 
**Intent Detection**  We apply maxpooling operation \( \text{Kim, 2014} \) on \( \hat{H}^{(L)} \) to obtain sentence representation \( c \), which is used as input for intent detection:

\[
\hat{y}^I = \text{softmax}(W^I c + b_S), \quad (14)
\]

\[
o^I = \text{argmax}(y^I), \quad (15)
\]

where \( \hat{y}^I \) is the output intent distribution; \( o^I \) represents the intent label and \( W^I \) are trainable parameters of the model.

**Slot Filling**  We follow E et al., 2019 to apply a standard CRF layer to model the dependency between labels, which is shown:

\[
O_S = W^S \hat{H}^{(L)}_S + b_S, \quad (16)
\]

\[
P(\hat{y}|O_S) = \frac{\sum_{i=1}^{m} \exp f(y_{i-1}, y_i, O_S)}{\sum_{y'} \sum_{i=1}^{m} \exp f(y'_{i-1}, y'_i, O_S)}, \quad (17)
\]

where \( y' \) represents an arbitrary label sequence, and \( f(y_{i-1}, y_i, O_S) \) computes the transition score from \( y_{i-1} \) to \( y_i \) and the score for \( y_i \).

**2.4 Joint Training**

Following Goo et al., 2018, intent detection and slot filling are optimized simultaneously via a joint learning scheme. A cross-entropy loss is used for intent detection:

\[
L_1 \triangleq -\sum_{j=1}^{m} \hat{y}^I_j \log (y^I_j), \quad (18)
\]

Similarly, the slot filling objective is:

\[
L_2 \triangleq -\sum_{j=1}^{m} \sum_{i=1}^{n_j} \hat{y}_i^S \log (y_i^S), \quad (19)
\]

where \( \hat{y}^I_j \) and \( \hat{y}_i^S \) are the gold intent label and gold slot label, respectively; \( m \) is the number of training data and \( n_j \) is the number of tokens in \( j^{th} \) data.

The final joint objective is formulated as:

\[
L_\theta = \alpha L_1 + (1 - \alpha) L_2, \quad (20)
\]

where \( \alpha \) is hyper-parameter.

**3 Experiments**

**3.1 Dataset**

We conduct experiments on two benchmark datasets. One is the public ATIS dataset (Hemphill et al., 1990) containing audio recordings of flight reservations, and the other is the custom-intent-engines collected by Snips (SNIPS dataset) (Coucke et al., 2018). ATIS has 4478 utterances for training, 500 for validation, and 893 utterances for testing. SNIPS has 13084 utterances for training, 700 for validation, and 700 for testing. Both datasets are used in our paper following the same format and partition as in Goo et al., 2018 and Qin et al., 2019.

**3.2 Experimental Settings**

The hidden units of the shared encoder and the co-interactive module are set as 128. We use 300d GloVe pre-trained vector (Pennington et al., 2014) as the initialization embedding. The number of co-interactive module is 2. L2 regularization used on our model is \( 1 \times 10^{-6} \) and the dropout ratio of co-interactive module is set to 0.1. We use Adam (Kingma and Ba, 2014) to optimize the parameters in our model. For all the experiments, we select the model which works the best on the dev set, and then evaluate it on the test set.
Table 1: Slot filling and intent detection results on two datasets. The numbers with * indicate that the improvement of our model over all baselines is statistically significant with p < 0.05 under t-test.

| Model | SNIPS | ATIS |  |
|-------|-------|------|------|
|       | Slot (F1) | Intent (Acc) | Overall (Acc) | Slot (F1) | Intent (Acc) | Overall (Acc) |
| Slot-Gated Atten [Goo et al., 2018] | 88.8 | 97.0 | 75.5 | 94.8 | 93.6 | 82.2 |
| Self-Attentive Model [Li et al., 2018] | 90.0 | 97.5 | 81.0 | 95.1 | 96.8 | 82.2 |
| Bi-Model [Wang et al., 2018] | 93.5 | 97.2 | 83.8 | 95.5 | 96.4 | 85.7 |
| CAPSULE-NLU [Zhang et al., 2019] | 91.8 | 97.3 | 80.9 | 95.2 | 95.0 | 83.4 |
| SF-ID Network [E et al., 2019] | 90.5 | 97.0 | 78.4 | 95.6 | 96.6 | 86.0 |
| CM-Net [Liu et al., 2019] | 93.4 | 98.0 | 84.1 | 95.6 | 96.1 | 85.3 |
| Stack-Propagation [Qin et al., 2019] | 94.2 | 98.0 | 86.9 | 95.9 | 96.9 | 86.5 |
| Our framework | 95.9* | 98.8* | 90.3* | 95.9 | 97.7* | 87.4* |

Table 2: Ablation experiments on the Snips and ATIS datasets.

| Model | SNIPS | ATIS |  |
|-------|-------|------|------|
|       | Slot (F1) | Intent (Acc) | Overall (Acc) | Slot (F1) | Intent (Acc) | Overall (Acc) |
| without intent attention layer | 95.8 | 98.5 | 90.1 | 95.6 | 97.4 | 86.6 |
| without slot attention layer | 95.8 | 98.3 | 89.4 | 95.5 | 97.6 | 86.7 |
| self-attention mechanism | 95.1 | 98.3 | 88.4 | 95.4 | 96.6 | 86.1 |
| with intent-to-slot | 95.6 | 98.4 | 89.3 | 95.8 | 97.1 | 87.2 |
| with slot-to-intent | 95.4 | 98.7 | 89.4 | 95.5 | 97.7 | 87.0 |
| without FFN | 95.7 | 98.4 | 89.1 | 95.7 | 97.3 | 87.0 |
| Our framework | 95.9 | 98.8 | 90.3 | 95.9 | 97.7 | 87.4 |

3.3 Baselines

To validate the performance of the proposed model, we compare our model with the existing baselines including: 1) Slot-Gated Atten. Goo et al., 2018] proposed the slot-gated joint model to leverage the intent information to guide the slot filling task. 2) Self-Attentive Model. Li et al., 2018] proposed a novel self-attentive model with the intent augmented gate mechanism to utilize the semantic correlation between slot and intent. 3) Bi-Model. Wang et al., 2018] proposed two separate BiLSTM to consider the cross-impact between the two tasks. 4) CAPSULE-NLU. Zhang et al., 2019] proposed a capsule-based neural network model to accomplish slot filling and intent detection. 5) SF-ID Network. E et al., 2019] introduced an SF-ID network with an iterative mechanism to establish connection between slot and intent. 6) CM-Net. Liu et al., 2019] proposed a novel collaborative memory network (CM-Net) for jointly modeling slot filling and intent detection. 7) Stack-Propagation. Qin et al., 2019] proposed a stack-propagation framework with token-level intent detection to better apply intent information to guide slot filling task and achieve the state-of-the-art performance.

For the Slot-gated Atten, CAPSULE-NLU, SF-ID Network and Stack-Propagation, we adopt the reported results from Qin et al., 2019]. For the CM-Net, we re-implemented the models and obtained the results on the same datasets because they did not release their code.

3.4 Main Results

Following Goo et al., 2018] and Qin et al., 2019], we evaluate the performance of slot filling using F1 score, intent prediction using accuracy, the sentence-level semantic frame parsing using overall accuracy which represents all metrics are right in an utterance. Table 1 shows the experiment results of the proposed models on the SNIPS and ATIS datasets.

From the results, we have the following observations: 1) We can see that our model significantly outperforms all baselines by a large margin and achieves the state-of-the-art performance, which demonstrates the effectiveness of our proposed co-interactive attention network. Especially, our framework gains the largest improvements on sentence-level semantic frame accuracy, which indicates that our co-interactive network successfully grasps the relationship between the intent and slots and improve the SLU performance. 2) Compared with baselines Slot-Gated, Self-Attentive Model and Stack-Propagation that are only leverage intent information to guide the slot filling, our framework gain a large improvement. We attribute it to the reason that our framework consider the cross-impact between the two tasks where the slot information can be used for improving intent detection. 3) Bi-Model, SF-ID Network,
Table 3: The SLU performance on BERT-based model on two datasets.

| Model                               | SNIPS          | ATIS           |
|-------------------------------------|----------------|----------------|
|                                     | Slot (F1)      | Intent (Acc)   | Overall (Acc) | Slot (F1)      | Intent (Acc)   | Overall (Acc) |
| Our framework                       | 95.9           | 98.8           | 90.3          | 95.9           | 97.7           | 87.4          |
| sparse + ConveRT (Bunk et al., 2020)| 94.8           | 96.8           | 95.1          | 95.1           | 96.6           | 88.2          |
| BERT SLU (Chen et al., 2019)        | 97.0           | 98.6           | 92.9          | 96.1           | 97.5           | 88.6          |
| Stack-Propagation + BERT  (Qin et al., 2019) | 97.0   | 99.0           | 92.9          | 96.1           | 97.5           | 88.6          |
| Our framework + BERT                 | 97.1           | 98.8           | 93.1          | 96.1           | 98.0           | 88.8          |

Figure 3: Visualization of two co-interactive attention layers. (a) The first layer. (b) The second layer.

and CM-Net also can be seen as considering the mutual interaction between the two tasks. Nevertheless, their models cannot model the cross-impact simultaneously, which limits their performance and their models even underperform the Stack-Propagation that only considers the single information flow from intent to slot. Our framework outperforms CM-Net by 6.2% and 2.1% on overall acc on SNIPS and ATIS dataset, respectively. We think the reason is that our framework achieves the bidirectional connection simultaneously in a unified network.

3.5 Analysis

3.5.1 Effect of Label Attention Layer

In this section, we set up the following ablation experiments to study the impact of the label attention layer.

Impact of Explicit Intent Representations We remove the intent attention layer and replace $H_I$ with $H$. This means that we only get the slot representation explicitly, without the intent semantic information. We refer it as without intent attention layer. The result is shown in Table 2 from the result of without intent attention layer, we observe the slot filling and intent detection performance drops, which demonstrates that the initial explicit intent and slot representations are critical to the co-interactive layer between the two tasks.

Impact of Explicit Slot Representations Similarly, we remove the slot attention layer and replace $H_S$ with $H$. This means that we only get the intent representation explicitly, without the slot semantic information. We name it as without slot attention layer. The results are shown in Table 2. From the result of without slot attention layer, 0.9% and 0.7% overall acc drops on SNIPS and ATIS dataset, respectively. This again verifies that the obtained explicit intent and slot representations are useful for better mutual interaction.

3.5.2 Effect of Co-Interactive Attention Layer

To verify the effectiveness of the proposed co-interactive layer, we conduct experiments with following ablations:

Co-Interactive Attention vs. Self-Attention Mechanism We use the self-attention layer in vanilla Transformer instead of the co-interactive layer in our framework, which can be seen as no explicit interaction between the two tasks. Specifically, we concatenate the $H_S$ and $H_I$ output from the label attention layer as input, which are fed into self-attention module. The results are shown in 2 we observe that our framework outperforms the self-attention mechanism. We believe the reason is that self-attention mechanism can only model the interaction implicitly while our co-interactive layer can explicitly consider the cross-impact between slot and intent, which makes our framework make full use of the mutual interaction knowledge.
**Bidirectional Connection vs. One Direction Connection (Intent-to-Slot)** We only keep one direction of information flow from intent to slot, which means that we only use the intent representation as queries to attend the corresponding slot representations. We name it as *with intent-to-slot*.

**Bidirectional Connection vs. One Direction Connection (Slot-to-Intent)** Similarly, we only keep one direction of information flow from slot to intent, which means that we only use the slot representation as queries to attend the corresponding intent representations. We name it as *with slot-to-intent*.

We observe that our framework outperforms *with intent-to-slot* and *with slot-to-intent*. We attribute it to the reason that modeling the mutual interaction between slot filling and intent detection can enhance the two tasks in a mutual way. In contrast, their models only consider the interaction from single direction of information flow and ignore the information of another task and limit their performance.

### 3.5.3 Effect of FFN Layer

We further investigate the effectiveness of the FFN layer in our framework. We conduct experiments by removing the FFN layer and we name it as *without FFN*. FFN aims to further fuse the intent and slot information with an implicit way. The experimental results show that all metrics drops, which verifies the effectiveness of the FFN layer. The reason is that the implicit fusion of the interactive slot and intent representations will further enhance the interaction between the two tasks, which is useful for slot filling and intent detection.

### 3.5.4 Visualization

To better understand what the model has learnt, we visualized the co-interactive attention layer. In particular, we visualized the attention distribution of the intent representation to each token of slot representation. From Figure 3, we can observe: (1) our model properly attend the corresponding slot token “movies” and “mann theatres” at intent “SearchScreeningEvent” where the attention weights successfully focus on the correct slot. This indicates that our co-interactive attention layer can learn to attend the corresponding slots at specific intent. (2) Using deeper layers could better help model to capture related slots and intent, the attention score is getting darker compared with the first layer. This is because that the stacked co-interactive module achieves to capture mutual interaction knowledge gradually.

### 3.5.5 Effect of Layer Number

In the section, we explore the impact of the stack number of the co-interactive module. The comparison experiments are shown in Figure 4. We can see that using deeper layers could generally lead to better performance, especially when the number of stacked layers is less than three. It is because the stacked co-interactive layer can better model the interaction between two tasks and learn mutual knowledge. When the number of stacked layers exceeds two, the experimental performance gets worse. We suggest that the reason might lie in the gradient vanishing or overfitting problem as the whole network goes deeper.

### 3.5.6 Effect of BERT

We follow Qin et al., 2019) to explore BERT (Devlin et al., 2018), in our framework. We replace the shared encoder by BERT base model with the fine-tuning approach and keep other components as same with our framework. The results are shown in Table 3. We can see: 1) BERT model performs remarkably well on both two datasets and obtains a large improvement against our basic framework,
which demonstrates the effectiveness of a strong pre-trained model in SLU tasks. This is consistent with the observation (Qin et al., 2019). 2) Our framework + BERT outperforms the BERT SLU (Chen et al., 2019) and Stack-Propagation +BERT, which verifies the effectiveness of our proposed framework whether it’s based on BERT or not and indicates that our framework works orthogonal with BERT.

4 Related Work

Intent detection can be treated as a classification task. Different classification methods, such as support vector machine (SVM) and RNN (Haffner et al., 2003; Sarikaya et al., 2011), have been proposed to solve it. Xia et al., 2018) adopts a capsule-based neural network with self-attention for intent detection. Slot filling can be seen as the sequence labeling task and the popular methods are conditional random fields (CRF) (Raymond and Riccardi, 2007) and recurrent neural networks (RNN) (Xu and Sarikaya, 2013; Yao et al., 2014).

Recently, many dominant joint models (Liu and Lane, 2016; Zhang and Wang, 2016; Goo et al., 2018; Li et al., 2018; Qin et al., 2019) are proposed to consider the closely correlated relationship between the two tasks. Existing joint work can be mainly classified into two classes. A series of work adopts multi-task framework to model the relationship between slots and intent. Zhang and Wang, 2016) proposes a shared RNN encoder to capture the shared feature between the two tasks. Liu and Lane, 2016) further propose an attention mechanism to better model the relationship. Compared with their work, our framework explicitly model the interaction with a proposed co-interactive module between the two tasks while their model only implicitly model the relationship by sharing parameters. In addition, the proposed co-interactive module can be stacked to better capture the mutual interaction knowledge. Another series of work explicitly leverages intent information to guide slot filling task. Goo et al., 2018) and Li et al., 2018) propose a gate mechanism to explicitly apply intent information for slot filling. Qin et al., 2019) propose a stack-propagation framework and token-level intent detection mechanism to explicitly leverage intent information to guide slot filling, which achieves the state-of-the-art performance. Compared with our model, they only consider the single direction of information flow by passing the intent information to slot filling, which ignores to leverage the information of slot to guide intent detection. In contrast, we propose a co-interactive transformer framework, which considers the cross-impact and establish a directional connection between the two tasks.

Recently, Wang et al., 2018), E et al., 2019), and Liu et al., 2019) propose model to promote slot filling and intent detection via mutual interaction. Compared with their methods, the main difference are as following: 1) Wang et al., 2018) propose two separate module for the two tasks to consider the cross-impact while our framework adopt the shared encoder to capture the shared knowledge between slot and intent, which can not only better capture the shared knowledge but also alleviate the error propagation. 2) E et al., 2019) introduce a SF-ID network, which includes two sub-networks iteratively achieve the flow of information between intent and slot. Compared with their models, our framework build a bidirectional connection between the two tasks simultaneously in an unified framework while their frameworks must consider the iteratively task order. 3) Liu et al., 2019) propose a collaborative memory block to implicitly consider the mutual interaction between the two tasks, which limits their performance where their models even underperform Stack-propagation model (Qin et al., 2019). In contrast, our framework proposes a co-interactive attention module to explicitly establish the bidirectional connection between the two tasks, which leads to more interpretable. 4) To the best of our knowledge, we are the first work to establish bidirectional connection between two tasks simultaneously with an explicit way in an unified framework.

5 Conclusion

In our paper, we propose a co-interactive transformer to joint model slot filling and intent detection to build a directional connection between the two tasks, which enables to fully take the advantage of the mutual interaction knowledge. In addition, the proposed co-interactive module can be stacked to gradually better model the mutual interaction. Experiments on two datasets show the effectiveness of the proposed models and our framework achieves the state-of-the-art performance. Besides, we explore and analyze the effect of BERT in our framework. With BERT, our framework reaches a new best result.
**References**

Ba, J. L., Kiros, J. R., and Hinton, G. E. (2016). Layer normalization.

Bunk, T., Varshneya, D., Vlasov, V., and Nichol, A. (2020). Diet: Lightweight language understanding for dialogue systems. *arXiv preprint arXiv:2004.09936*.

Chen, Q., Zhuo, Z., and Wang, W. (2019). Bert for joint intent classification and slot filling. *arXiv preprint arXiv:1902.10909*.

Coucke, A., Saade, A., Ball, A., Bluche, T., Caulier, A., Leroy, D., Doumouro, C., Gisselbrecht, T., Caltagirone, F., Lavril, T., et al. (2018). Snips voice platform: an embedded spoken language understanding system for private-by-design voice interfaces. *arXiv preprint arXiv:1805.10190*.

Cui, L. and Zhang, Y. (2019). Hierarchically-refined label attention network for sequence labeling. In *Proc. of EMNLP*.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

E, H., Niu, P., Chen, Z., and Song, M. (2019). A novel bi-directional interrelated model for joint intent detection and slot filling. In *Proc. of ACL*.

Goo, C.-W., Gao, G., Hsu, Y.-K., Huo, C.-L., Chen, T.-C., Hsu, K.-W., and Chen, Y.-N. (2018). Slot-gated modeling for joint slot filling and intent prediction. In *Proc. of NAACL*.

Haffner, P., Tur, G., and Wright, J. H. (2003). Optimizing svms for complex call classification. In *In Proc. of ICASSP*.

Hemphill, C. T., Godfrey, J. J., and Doddington, G. R. (1990). The atis spoken language systems pilot corpus. In *Speech and Natural Language: Proceedings of a Workshop Held at Hidden Valley, Pennsylvania, June 24-27, 1990*.

Hochreiter, S. and Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, 9(8).

Kim, Y. (2014). Convolutional neural networks for sentence classification. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1746–1751, Doha, Qatar. Association for Computational Linguistics.

Kingma, D. P. and Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

Li, C., Li, L., and Qi, J. (2018). A self-attentive model with gate mechanism for spoken language understanding. In *Proc. of EMNLP*.

Liu, B. and Lane, I. (2016). Attention-based recurrent neural network models for joint intent detection and slot filling. *arXiv preprint arXiv:1609.01454*.

Liu, Y., Meng, F., Zhang, J., Zhou, J., Chen, Y., and Xu, J. (2019). CM-net: A novel collaborative memory network for spoken language understanding. In *Proc. of EMNLP*.

Pennington, J., Socher, R., and Manning, C. (2014). Glove: Global vectors for word representation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*.

Qin, L., Che, W., Li, Y., Wen, H., and Liu, T. (2019). A stack-propagation framework with token-level intent detection for spoken language understanding. In *Proc. of EMNLP*.

Raymond, C. and Riccardi, G. (2007). Generative and discriminative algorithms for spoken language understanding. In *Eighth Annual Conference of the International Speech Communication Association*.

Sarikaya, R., Hinton, G. E., and Ramabhadran, B. (2011). Deep belief nets for natural language call-routing. In *ICASSP*.

Tur, G. and De Mori, R. (2011). *Spoken language understanding: Systems for extracting semantic information from speech*. John Wiley & Sons.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L. u., and Polosukhin, I. (2017). Attention is all you need. In *NIPS*.
Wang, Y., Shen, Y., and Jin, H. (2018). A bi-model based rnn semantic frame parsing model for intent detection and slot filling. In Proc. of ACL.

Xia, C., Zhang, C., Yan, X., Chang, Y., and Yu, P. (2018). Zero-shot user intent detection via capsule neural networks. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 3090–3099, Brussels, Belgium. Association for Computational Linguistics.

Xu, P. and Sarikaya, R. (2013). Convolutional neural network based triangular crf for joint intent detection and slot filling. In 2013 IEEE Workshop on Automatic Speech Recognition and Understanding.

Yao, K., Peng, B., Zhang, Y., Yu, D., Zweig, G., and Shi, Y. (2014). Spoken language understanding using long short-term memory neural networks. In SLT.

Zhang, C., Li, Y., Du, N., Fan, W., and Yu, P. (2019). Joint slot filling and intent detection via capsule neural networks. In Proc. of ACL.

Zhang, X. and Wang, H. (2016). A joint model of intent determination and slot filling for spoken language understanding. In Proc. of IJCAI.