An Effective Non-Autoregressive Model for Spoken Language Understanding

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ABSTRACT
Spoken Language Understanding (SLU), a core component of the task-oriented dialogue system, expects a shorter inference latency due to the impatience of humans. Non-autoregressive SLU models clearly increase the inference speed but suffer uncoordinated-slot problems caused by the lack of sequential dependency information among each slot chunk. To gap this shortcoming, in this paper, we propose a novel non-autoregressive SLU model named Layered-Refine Transformer, which contains a Slot Label Generation (SLG) task and a Layered Refine Mechanism (LRM). SLG is defined as generating the next slot label with the token sequence and generated slot labels. With SLG, the non-autoregressive model can efficiently obtain dependency information during training and spend no extra time in inference. LRM predicts the preliminary SLU results from Transformer’s middle states and utilizes them to guide the final prediction. Experiments on two public datasets indicate that our model significantly improves SLU performance (1.5% on Overall accuracy) while substantially speed up (more than 10 times) the inference process over the state-of-the-art baseline.

CCS CONCEPTS
• Computing methodologies → Natural language processing.

KEYWORDS
Multi-Task Learning, Spoken Interfaces, Task-Oriented Dialogue System
of the SF task [30]. The reason is that SF is a sequence labeling task whose results utilize the “Inside–Outside–Beginning (IOB)" tagging format. Therefore, SF heavily depends on the strongness of the sequential dependency information among each slot chunk (proved by [25]). However, the slot labels are predicted independently and simultaneously in self-attention based methods, which reduces the strongness of the sequential dependency and causes the uncoordinated slot problem. Figure 2 shows an example of the uncoordinated slot problem, where B-city should be followed by I-city, but I-time is predicted by mistake. Therefore, how to maintain the non-autoregressive efficiency when inferring while increase the sequential dependency information to avoid the uncoordinated problem in SLU tasks is a major challenge.

![Correct Slots](image1)

![Uncoordinated Slots](image2)

**Figure 2: An example of uncoordinated slot problem.**

Although Wu et al. [30] tries to handle this problem via a two-pass mechanism called SlotRefine, this method still has the following weakness: First, SlotRefine supposes all the uncoordinated slot problems are caused by wrong ‘I-tags’ and only utilize ‘B-tags’ to correct the ‘I-tags’ in its second pass period. However, as shown in Figure 2, when predicting, an incorrect ‘B-tag’ follows by a correct ‘I-tag’ also happens. In this case, SlotRefine cannot utilize ‘I-tags’ to correct the ‘B-tags’. Second, the two-pass mechanism needs to characterize text and predict two times in both the training and testing process, which inevitably leads to lower efficiency. Therefore, how to use the prediction results for interactive feedback to improve the overall performance while avoiding inferring the entire model repeatedly is also a significant challenge.

To solve the above challenges, in this paper, we propose a Layered-Refine Transformer (LR-Transformer) framework for SLU, which contains a Slot Label Generation (SLG) auxiliary task and a Layered Refine Mechanism (LRM) based on the Transformer. Specifically, SLG is an auxiliary task defined as predicting the next SF label according to the utterance sequence and generated SF labels, which is an autoregressive process like the machine translation. We jointly train the SLG and the original sequence labeling-based SLU tasks by multi-task learning and share their encoder. By SLG, the shared encoder learns more sequential dependency information from the decoder through the cross attention mechanism in the Transformer and further improves sequence labeling-based SLU tasks. Notable, SLG is only employed in the training process and consumes no extra inference time. Thus our model is still a fast non-autoregressive model. LRM modifies the hidden states between Transformer layers according to the intermediate predicted ID and SF results to help the final prediction. More specifically, LRM predicts the preliminary results of ID and SF by the hidden states of the former Transformer layer, merging the result embeddings with the hidden states and inputting them into the next Transformer layer. We have further proved in experiments that LRM only needs to be employed once and does not need to be used between every Transformer layer, so the cost is much smaller than running the entire model twice.

The main contributions of this paper are presented as follows:

1. We design the SLG as auxiliary multitasking of SLU, which increases the sequential dependency information of the model while consuming no extra inference time.
2. We propose the LRM, which improves the overall performance of SLU tasks by the interaction of predicted results between Transformer layers. Compared with running the entire model twice, the cost of LRM is much smaller.
3. Experimental results on two public datasets show our model is superior to both existing SOTA autoregressive and non-autoregressive models in terms of speed and performance, indicating that our model has great potential for real-world application.

## 2 RELATED WORK

In this section, we introduce some joint learning and multi-task learning approaches utilized in SLU.

In SLU, intent detection is usually seen as a semantic classification problem to predict the intent label, and slot filling is mainly regarded as a sequence labeling task. Early studies [14, 20, 21, 32] usually regard ID and SF as two separate tasks and utilize pipeline approaches to manage these two tasks. These methods typically suffer from error propagation due to their independent models and prove less effective than the joint models.

Recently, some work finds that ID and SF are closely related. Goo et al. [8] propose a slot-gated model that learns the relationship between intent and slot by the gate mechanism. Inspired by [8], some bi-directional networks are proposed [9, 19], which dig into the correlation between ID and SF deeper and model the relationship between them more explicitly. In the above work, the interrelated connections between ID and SF are established. Besides, Zhang et al. [33] utilize a hierarchical capsule neural network structure encapsulating the hierarchical relationship among utterance, slot, and intent. Qin et al. [23] propose a Stack-Propagation framework that uses result information of ID to guide the SF task but ignores the impact of SF results on the ID task. Although Stack-Propagation reaches the SOTA performance on two SLU datasets, it surfs a long inference latency caused by the heavy and complex framework. Qin et al. [24] then concern about the impact of SF results in their model but still suffering the long inference latency. Inspired by [31], Cheng et al. [4] propose a portable framework RPFSLU, which contains a two-round predicting period. RPFSLU utilizes the semantic information of the first round prediction results to guide
the second round prediction by a represent learning process. However, although RPP-SL is portable, it is not a lightweight model due to its two-round prediction process.

The above methods mostly use the autoregressive models (e.g., LSTM and GRU [5]) that suffer inevitable long inference latency. Inspired by the well performance of Transformer in other tasks [15, 16, 18, 19], Wu et al. [30] then propose a non-autoregressive joint learning approach for multi-turn SLU, which speeds up the predicting process and encounters the uncoordinated-slot problem. SlotRefine tries to handle this problem by a two-pass refine mechanism and get some effect. However, it still suffers uncoordinated slot problems caused by the wrong ‘I-tag’ and not efficient enough during inference due to its two-pass mechanism that needs to run the whole model twice.

Meanwhile, some work [10, 22] tries to enhance the performance via multi-task learning. These multi-task learning methods link the two tasks implicitly via applying a joint loss function. Bai et al. [1] propose an impressive multi-task learning approach for multi-turn SLU by consolidating context memory with a dialogue logistic classifier that our model has great potential for industrial application.

In this section, we first introduce the basic model of our LR-Transformer. Secondly, we introduce the Layered Refine Mechanism.

3 METHOD

In this section, we introduce the problem formulation and describe our basic model in detail.

The input of SLU tasks is an utterance composed by a token sequence \( X = \{x_1, \ldots, x_n\} \), where \( n \) donates the sequence length. Given \( X \) as input, our tasks are composed of Intent Detection (ID) and Slot Filling (SF). Specifically, ID is a semantic classification task to predict the intent label for the whole utterance, while SF is a sequence labeling task to give each token in the sequence a slot label. In our model, the intent label and all slot labels are predicted simultaneously.

Following previous non-autoregressive models, we employ the multi-head Transformer encoder [29] as our basic model. Vaswani et al. [29] describe the Transformer framework in great detail, so we do not need to introduce it again. The only difference is that we utilize self-attention with relative position representations [27] to address the sequential information.

Akin to the operation in BERT [7], we first insert a special token ‘CLS’ in the beginning of the token sequence, which is utilized to predict the label of the intent. Given the new sequence \( X = \{x_{CLS}, x_1, \ldots, x_n\} \) as input, the Transformer encoder returns the hidden states sequence \( H = \{h_{CLS}, h_1, \ldots, h_n \in \mathbb{R}^{d_{model}}\} \) as output, where \( d_{model} \) is the input and output dimension of the Transformer layer. Then, the prediction of ID and SF are calculated as:

\[
\begin{align*}
    y^I &= \text{softmax}(W^I \cdot h_{CLS} + b^I) \\
    y^S &= \text{softmax}(W^S : (h_j \oplus h_{CLS}) + b^S)
\end{align*}
\]

where \( y^I \in \mathbb{R}^{d_i} \) and \( y^S = \{y_1^S, \ldots, y_n^S \in \mathbb{R}^{d_s}\} \) donate the results of ID and SF, \( d_i \) and \( d_s \) are the the categories of the intent label and slot labels, \( W^I \in \mathbb{R}^{d_i \times d_{model}} \) and \( W^S \in \mathbb{R}^{d_s \times 2d_{model}} \) are fully connected matrices, \( b^I \in \mathbb{R}^{d_i} \) and \( b^S \in \mathbb{R}^{d_s} \) are bias vectors, and \( \oplus \) donates the concatenation operation.

The objective of our basic model can be formulated as:

\[
    p\left(y^I, y^S \mid X\right) = \prod_{j=1}^{n} p\left(y_j^S \mid X, y^I\right)
\]

The joint loss function of SLU is defined as:

\[
    L_{SLU} = - \sum_{j=1}^{n} \log P(y_j^I \mid x_1, \ldots, x_n)
\]
We design the LRM which works between two Transformer layers where \( \lambda \) is a hyper-parameter.

In practice, we extend our basic model with a Transformer decoder [29] to construct the model architecture of SLG. The complete framework of SLG works as a sequence to sequence (seq2seq) model. Since the Transformer-based seq2seq model has been widely used, we do not describe it in more detail.

Moreover, to enhance the prediction consistency between the SLU task and the SLG task, we further design a consistency loss function based on the cross entropy. The final loss function of SLG is defined as:

\[
\mathcal{L}_{SLG} = (1 - \alpha) \cdot -\log P(y^G \mid X) + \alpha \cdot H(y^G, y^S) = (\alpha - 1) \cdot -\log P(y^G \mid X) + \alpha \cdot H(y^G, y^S)
\]

where \( H \) is the cross-entropy function, \( \alpha \) is a hyper-parameter and \( y^S \) is the predicted labels of SF obtained by Eq.1.

By SLG, the shared encoder can learn more sequential dependency information from the decoder through the cross attention mechanism in Transformer and further improve sequence labeling-based SLU tasks.

The loss function of overall multi-task learning is defined as:

\[
\mathcal{L} = \mathcal{L}_{SLU} + \lambda \mathcal{L}_{SLG}
\]

where \( \lambda \) is a hyper-parameter.

Notably, the SLG task is only carried out during the training process and costs no extra time for inference. Therefore, our SLU model is still a non-autoregressive model, which is very efficient.

### 3.3 Layered Refine Mechanism

In this section, we introduce the Layered Refine Mechanism (LRM) for the Transformer in detail.

Previous work [4] has widely proved that ID and SF are closely related. Taking advantage of the correlation between these two tasks, especially utilizing one task’s results in the other, can effectively enhance the overall performance. However, since the non-autoregressive approach predicts the results of ID and SF simultaneously, we can not directly employ these results in a one-pass prediction process like Stack-Propagation [23] do. Although we can utilize a two-pass mechanism to generate the first-pass results and guide the second-pass prediction via them, it is a trade-off between autoregression and non-autoregression, which costs much time.

Considering Transformer contains a multi-layer architecture, and each encoder layer of the Transformer has the same structure. We design the LRM which works between two Transformer layers and utilizes middle states of the Transformer to guide the final prediction.

Specifically, we first predict a preliminary results of ID \( \tilde{y}^I \) and SF \( \tilde{y}^S = \{\tilde{y}^S_0, ..., \tilde{y}^S_n\} \) by Eq.1 according to hidden states \( \mathbf{H}^k = \{\mathbf{h}^k_{cls}, \mathbf{h}^k_1, ..., \mathbf{h}^k_n\} \) from the \( k \)-th Transformer layer. Then, we embed \( \tilde{y}^I \) into \( e^I \in \mathbb{R}^{d_e} \) and \( \tilde{y}^S = \{\tilde{y}^S_0, ..., \tilde{y}^S_n\} \) into \( e^S = \{e^S_1, ..., e^S_n\} \in \mathbb{R}^{d_e} \) by the embedding layer, respectively, where \( d_e \) is the embedding size and we set \( d_e = d_{model} \) in this paper.

Since the SF returns a sequence of result embedding vectors, we further calculate the weighted average of those embedding vectors via an attention mechanism to obtain an utterance-level result embedding vector \( e^S_0 \) by

\[
e^S_0 = \sum_{j=1}^{n} \alpha_j \cdot e^S_j
\]

where \( \alpha_j \) is the weight of \( e^S_j \) obtained by

\[
\alpha_j = \frac{\exp(e^S_j)}{\sum_{k=1}^{n} \exp(e^S_k)}
\]

By the above calculation, we obtain result embedding vectors \( e^I \), \( e^S \) and \( e^S_0 \), which contain semantic information from the preliminary results of ID and SF. Subsequently, we merge these vectors with the former output and obtain a new hidden states sequence \( \mathbf{H}' = \{\mathbf{h}'_{cls}, \mathbf{h}'_1, ..., \mathbf{h}'_n\} \) by

\[
\mathbf{h}'_{cls} = \mathbf{h}'_{cls} + e^I + e^S_0
\]

\[
\mathbf{h}'_j = \mathbf{h}'_j + e^S_j
\]

We use \( \mathbf{H}' \) as input of the \( k + 1 \)-th Transformer layer.

LRM can incorporate the bidirectional semantic information from one task to the other by propagating the combination of former output and preliminary results so that ID and SF become more accurate. The complete Markov chain process can be simplified as follows:

\[
p(y^I, y^S \mid X) = p(y^I \mid X) \cdot p(y^S \mid X, y^I) \cdot p(y^I \mid X, y^I, y^S, y^I)
\]
LRM is a portable plugin for the Transformer, which can be utilized between two Transformer encoder layer intervals. Actually, using LRM once in the whole Transformer structure is enough because it already considers the interaction between ID and SF. On the contrary, overusing LRM will make the Transformer layers lose their own feature and negatively affect the final performance because we use the SLU classifier in LRM. Also, LRM is not suitable for the autoregressive SLG task because it uses all SLU prediction labels simultaneously.

Besides, the network structure of LRM is mainly composed of a fully connected layer as the SLU classifier and an embedding layer for result embedding. Therefore, our LRM is very lightweight and consumes very little inference time.

4 EXPERIMENT

In this section, we demonstrate the effectiveness of LR-Transformer. We first introduce datasets, the necessary hyper-parameters, and the baselines used in our experiments. Then, we compare the performance of our framework with baselines and analyze the experiment results. Subsequently, we analyze the error caused by the uncoordinated problem and carry out an ablation study to verify the effectiveness of SLG and LRM. Finally, we combine our model with the pre-trained model and analyze the effect.

4.1 Experimental Settings and Baselines

| Dataset | ATIS | SNIPS |
|---------|------|-------|
| Vocabulary Size | 722 | 11241 |
| Avg. tokens per utterance | 11.28 | 9.05 |
| Intent categories | 21 | 7 |
| Slot categories | 120 | 72 |
| Training set size | 4478 | 13084 |
| Validation set size | 500 | 700 |
| Test set size | 893 | 700 |

Table 1: Dataset statistics.

Dataset: To evaluate the efficiency of our proposed model, we conduct experiments on two public datasets, i.e., ATIS (Airline Travel Information Systems [11]) and SNIPS (collected by Snips personal voice assistant [6]). Compared with ATIS, the SNIPS dataset is more complex due to its large vocabulary size, cross-domain intents, and more out-of-vocabulary words. The statistics of ATIS and SNIPS are shown in Table 1.

Evaluation Metrics: Following previous work, we evaluate the SLU performance of ID by accuracy and the performance of SF by the F1 score. Besides, we utilize overall accuracy to indicate the proportion of utterance in the corpus whose slots and intent are both correctly predicted. Usually, a higher intent accuracy and F1 score also lead to higher overall accuracy. However, this does not always happen, e.g., when the prediction contains more mistakes, but most mistakes are from the same utterances.

Set up: Following previous work, we use Adam [13] to optimize the parameters in our model and adopted the suggested learning rate of 0.001. The batch size is set to 32 according to the size of training data.

When tuning hyper-parameters, we repeat the model 5 times and select the parameters with the best average performance on the validation set as the optimal.

We first select the hyper-parameters used in our basic model. To select Transformer input and output size $d_{\text{model}}$, and the size of inner-layer in the feed-forward network of Transformer (we call it $d_{ff}$ in the following part), we leverage the grid search. Specifically, we determine $d_{\text{model}}$ in the range of {128, 256, 512} and $d_{ff}$ in the range of {128, 256, 512, 768}. We finally choose $d_{\text{model}}$ as 128 and $d_{ff}$ as 512 as the optimal. For other hyper-parameters of Transformer, following [29], we set both encoder and decoder layers as 6, the number of attention heads as 8, and the dropout ratio as 0.3. We utilize LRM once between the second and the third Transformer layer.

Then, we choose the hyper-parameters $\alpha$ used in Eq.5 and $\lambda$ used in Eq.6. We first fix $\lambda$ as 1 and select $\alpha$ in the range of (0,0.5] with the step 0.05. Subsequently, with the selected $\alpha$, we select $\lambda$ in range of [0,1) with the step 0.25. We finally get the optimal when $\alpha$ is 0.35 and $\lambda$ is 0.75. We will introduce the influence of $\lambda$ and $\alpha$ in our ablation study.

Baselines: We compare our model with the existing baselines, including:

- Joint Seq [10]: A GRU [5] based model with a multi-task modeling approach.
- Attention-BiRNN [17]: A LSTM [12] based encoder-decoder model with an intent attention mechanism.
- Slot-gated [8]: A LSTM based joint model together with a slot-gated mechanism as a special gate function.
- SF-ID [9]: A LSTM based joint model with cross-impact calculating between two tasks.
- Stack-Propagation [23]: A LSTM based joint model with stack-propagation framework and token-level ID. This model has already guided SF by ID results, which is the state-of-the-art of the joint model.
- Basic model: The encoder of Transformer framework with relative position representations Vaswani et al. [29].
- SlotRefine [30]: A Transformer based non-autoregressive model with a two-pass refine mechanism.

For Joint Seq, Attention BiRNN, Slot-gated, SF-ID, and Stack-Propagation, we adopt the reported results from [23]. For SlotRefine [30], since the benchmark in their original paper is calculated nonstandardly according to their open-source code, we re-implemented the model (all hyper-parameters strictly identical as [30]) and obtained the results. Note that, for SlotRefine, basic model, and LR-Transformer, we repeat the experiment 5 times and report the average as the final results.

4.2 Result and Analysis

In this section, we show the results of our experiments and do some analysis.
Table 2: SLU performance on ATIS and SNIPS 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 | ATIS | SNIPS |
|-------|------|-------|
|       | Intent | Slot | Overall | Intent | Slot | Overall |
| Joint Seq [10] | 92.6 | 94.2 | 80.7 | 96.9 | 87.3 | 73.2 |
| Attention-BiRNN [17] | 91.1 | 94.2 | 78.9 | 96.7 | 87.8 | 74.1 |
| Slot-Gated [8] | 93.6 | 94.8 | 82.2 | 97.0 | 88.8 | 75.5 |
| SF-ID [9] | 97.8 | 95.8 | 86.8 | 97.4 | 92.2 | 80.6 |
| Stack-Propagation [23] | 96.9 | 95.9 | 86.5 | 98.0 | 94.2 | 86.9 |
| Non-autoregressive Models | | | | | | |
| SlotRefine [30] | 97.1 | 96.0 | 86.9 | 97.4 | 93.5 | 84.4 |
| Basic model | 96.8 | 95.2 | 85.6 | 96.1 | 92.8 | 82.1 |
| LR-Transformer | 98.2↑ | 96.1↑ | 87.2↑ | 98.4↑ | 94.8↑ | 88.4↑ |

SLU Performance: The experiment results of the proposed models on ATIS and SNIPS datasets are shown in Table 2. The results show that our model significantly outperforms all the baselines and achieves the best performance in all three metrics. Compared with the prior non-autoregressive model SlotRefine, our model enhances the performance by 1.1%(ID), 0.1%(SF), and 0.3%(Overall) on ATIS and 1.0%(ID), 1.3%(SF), and 4.0%(Overall) on SNIPS. Compared with the SOTA baseline Stack-Propagation, LR-Transformer also achieve improvement by 1.3%(ID), 0.2%(SF), and 0.7%(Overall) on ATIS and 0.4%(ID), 0.6%(SF), and 1.5%(Overall) on SNIPS. This indicates the effectiveness of our LR-Transformer.

Notably, without SLG and LRM, our basic model performs worse than both SlotRefine and Stack-Propagation, but LR-Transformer outperforms both of them with SLG and LRM. We attribute this enhancement to the fact that our SLG task effectively obtains the sequential dependency information, and LRM directly takes the explicit result information into consideration, which grasps the relationship between the intent and slots. We will conduct experiments for the ablation study in section 4.4 to further verify this idea.

Speed Up: The inference time of SLU models is shown in Table 3. All the models in this experiment are conducted with a single TITAN Xp GPU. From the table, we can obviously find that our model achieves significant speedup ($\times10.53$ on ATIS; $\times10.24$ on SNIPS) against the autoregressive SOTA model Stack-Propagation because all slot labels are calculated simultaneously in our non-autoregressive method.

More importantly, compared with the existing non-autoregressive model SlotRefine, our model reduces nearly 60% inference latency on SNIPS and more than 65% on ATIS. The reason for this phenomenon is that SlotRefine needs to run the whole model twice, including the embedding layer, Transformer, and the classifier. As a comparison, our model is lightweight and obtains the final SLU results with a one-period prediction. Thus, although our model contains more transformer layers, it is still significantly faster than SlotRefine. From Table 3, we can also find that utilizing LRM consumes only 3% extra inference time compared to without LRM. This indicates that LRM is a lightweight approach, which generates negligible time cost.

4.3 Error Analysis

In this section, we will analysis the error caused by uncoordinated slots.

![Figure 5: The number of uncoordinated slots on the validation set of SNIPS during training.](image)

We first visualize the number decrease of uncoordinated slots in the training process. As shown in Figure 5, the number of uncoordinated slots drops slow and inefficient for the basic model. For our LR-Transformer, the number of uncoordinated slots drops
To further analyze the error in SF tasks in detail, we show the statistics of slot error (i.e., incorrect slots) on the validation set of SNIPS after training 100 epochs. Specifically, we define the errors caused by the uncoordinated slot problem as “Unc. error”. The uncoordinated slots includes two cases, i.e., correct 'B-tag' followed wrong 'I-tag' and wrong 'B-tag' following correct 'I-tag'. We define the first case as “BI error” and the second case as "IB error", respectively.

The statistics show that the uncoordinated slot problem composes a big part of all slot errors. Without any approach to solving this problem, our basic model encounters 57 uncoordinated slots, composing 33.7% of all slot errors. In these uncoordinated slots, 31 are caused by the "BI error," while 26 are caused by the "IB error." The proportion of the "BI error" and the "IB error" is almost close.

Compared with the basic model, our LR-Transformer reduces 44 uncoordinated slots. The proportion of uncoordinated slots in all incorrect slot labels drops from 33.7% to 11.1%. Moreover, our LR-Transformer efficiently reduces both the BI error and the IB error simultaneously. The reducing proportion between the BI error and the IB error of our model is also close. This is mainly because our SLG effectively obtains sequential dependency while LRM considers both B-tag slots and I-tag slots. As a comparison, SlotRefine correct most uncoordinated slots caused by the "BI error" but still suffering "IB error." For SlotRefine, the ‘IB error’ proportion is much higher than ‘BI error’.

We provide an example for the case study. In Figure 6, we notice that the basic model suffers a serious uncoordinated slot problem, including both two cases, i.e., "BI error" and 'IB error’, respectively. SlotRefine solves ‘BI error’ but predicts incorrect slot labels in the "IB error" case due to the error propagation from the wrong B-tag label. Our model solves problems of both cases and predicts a correct slot label sequence.

Above all, our LR-Transformer indeed remedies the problem of the uncoordinated slots, leading to better performance on SF.

4.4 Ablation Study

In this section, we do an ablation study to verify the effectiveness of SLG and LRM in detail.

Effect of SLG: As shown in Table 5, compared with the basic model, the LR-Transformer w/o LRM (i.e., basic model + SLG) enhances the performance with a large margin. Specifically, SLG brings enhancement by 0.3% for ID, 1.1% for SF, and 1.0% for overall on ATIS while 1.6% for ID, 1.4% for SF, and 4.4% for overall on SNIPS. We attribute this improvement to the autoregressive structure of SLG, which brings sequential solid dependency information, making prediction more accurate.

Moreover, comparing LR-Transformer with LR-Transformer* and LR-Transformer w/o LRM with LR-Transformer w/o LRM*, we find that utilizing consistency loss function in Eq.5 brings a slight enhancement. More importantly, the consistency loss effectively reduces the standard deviation, especially on SF and overall. This is mainly because utilizing consistency loss can enhance the prediction consistency between the SLU task and the SLG task, which makes the model more stable. Moreover, compared with SF, the standard deviation on ID tasks is much lower. We consider the reason is ID contains fewer categories and easier to predict.

We further conduct experiments to study the impact of $\alpha$ on the SF performance. In this experiment, we keep the other settings and change the $\alpha$ from 0 to 0.5. According to the results shown in Figure 7, we find that the F1 scores change little when $\alpha$ increases.
Table 5: Performance (mean and standard deviation of the model repeated 5 times) comparison of each module in our model. Models with * represent not using consistency loss in Eq.5, i.e., \( \alpha = 0 \) in Eq.5.

| Model                        | ATIS Intent | ATIS Slot | ATIS Overall | SNIPS Intent | SNIPS Slot | SNIPS Overall |
|------------------------------|-------------|-----------|--------------|--------------|------------|---------------|
| Basic model [27]             | 96.8        | 94.8      | 85.3         | 96.1         | 92.8       | 82.1          |
| LR-Transformer w/o SLG       | 97.0,047    | 95.6,0123 | 86.1,082     | 98.0,094     | 93.6,0125  | 84.9,0216     |
| LR-Transformer w/o LRM*      | 97.0,049    | 95.9,0169 | 86.2,0216    | 98.6,0124    | 94.1,0249  | 86.3,0205     |
| LR-Transformer w/o LRM       | 97.0,047    | 95.9,0194 | 86.3,094     | 98.7,0047    | 94.0,047   | 86.5,094      |
| LR-Transformer*              | 98.0,047    | 96.1,0163 | 87.2,0141    | 98.7,0081    | 94.6,0169  | 88.2,0169     |

Figure 7: Impact of \( \alpha \) on the SF performance on the SNIPS validation set.

Figure 8: Impact of \( \lambda \) on the SF performance on the SNIPS validation set.

From 0 to 0.35, but the stand deviation drops continuously. Then, when \( \lambda \) is larger than 0.4, both the F1 score and the stand deviation get worse rapidly. We consider the large weight of \( \lambda \) makes the wrong prediction in SLU excessively affect the SLG task and bring negative effect since the predicted labels of SLU are not the same as the ground-truth labels.

Figure 9: SF performance comparison of using LRM in different Transformer encoder intervals on SNIPS validation set. 1-2 represents the interval of the 1st and the 2nd Transformer encoder layer, and so on.

As we introduced in section 3.3, LRM can be utilized in each two Transformer encoder layer intervals. Motivated by finding the best place to operate LRM, we conduct the experiment to compare SF performance on the validation set of SNIPS when using LRM in different Transformer encoder intervals. The experiment result is shown in Figure 9.

Figure 10: SF performance comparison of different LRM usage count on SNIPS validation set.

We further conduct experiments to evaluate SF performance for different usage count of LRM. As shown in Figure 10, the F1 score decreases rapidly when the usage count increases. It shows that utilizing LRM alone still enhances SLU performance on both two tasks. We attribute the improvement to the direct utilization of ID and SF preliminary results. The semantic information from both slot labels and ID labels enhances the performance when predicting.
on the validation set achieves a satisfying level when employing LRM once or twice and drops significantly with increasing usage count. This phenomenon indicates that employing LRM one time is enough, and overuse LRM will negatively influence SLU prediction. We have introduced the reason in section 3.3, using LRM once in the whole Transformer structure already considers the interaction between ID and SF. Overusing LRM will make the Transformer layers lose their own feature and negatively affect the final performance due to the utilization of the SLU classifier in LRM.

4.5 Effect of Pretraining

In this section, we conduct experiments to evaluate the ability of our model to combining the pretrained model.

Recently, some work builds their models based on large-scale pre-trained model BERT [7], which utilized billions of external corpus and tremendous model parameters. Since the number of BERT parameters is much more than ours, it is unfair to compare the performance of our model with them directly. Thus, we also combine our approaches with BERT to highlight the effectiveness of LR-Transformer.

To make better use of the pre-trained results of BERT, we retain the weights of the original BERT model and do not change the inner structure of BERT. Therefore, we only combine our SLG module with BERT. In practice, we employ BERT as the encoder and utilize the same Transformer decoder as we introduced in section 3.2. Then we fine-tune the complete model on the SLU dataset.

As shown in Table 6, our BERT+SLG outperforms all previous BERT-based models on all evaluation metrics. Compared with BERT-SLU, SLG brings an enhancement of 0.8%(ID), 0.1%(SF), and 0.5%(Overall) on ATIS dataset and 0.5%(ID), 0.1%(SF), and 0.3%(Overall) on SNIPS dataset. All of these improvements of our model are statistically significant with $p < 0.05$ under t-test.

Table 6: SLU performance of Bert-based models on ATIS and SNIPS datasets. The numbers with $\uparrow$ indicate that the improvement of our model over all baselines is statistically significant with $p < 0.05$ under t-test.

| Model          | ATIS          | SNIPS         |
|----------------|--------------|---------------|
|                | Intent Slot Overall | Intent Slot Overall |
| BERT-SLU [2]   | 97.5 96.1 88.2 | 98.6 97.0 92.8 |
| BERT + Stack-Propagation [23] | 97.5 96.1 88.6 | 99.0 97.0 92.9 |
| BERT + SlotRefine [30] | 97.7 96.1 88.6 | 99.0 97.0 92.9 |
| LR-Transformer | 98.2 96.1 87.2 | 98.4 94.8 88.4 |
| BERT+SLG       | 98.3↑ 96.2↑ 88.7↑ | 99.1↑ 97.1↑ 93.1↑ |

To sum up, our designed SLG task is well combined with the pre-trained model BERT, and BERT+SLG outperforms all existing models on both performance and inference latency.

5 CONCLUSION

In this paper, we propose a fast and accurate non-autoregressive model: LR-Transformer. To address the sequential dependency information among tokens, we design the SLG task, which effectively enhances the performance of SF through multi-task learning and costs no extra inference time. We also design a Layered Refine Mechanism, which guides the final prediction via the interaction of predicted results between Transformer layers. LRM explicitly introduces the correlation between ID and SF into the model with a little cost of time. Experiments on two public datasets indicate that our model significantly improves performance while substantially accelerate the inference speed.

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