

# MRRL: Modifying the Reference via Reinforcement Learning for Non-Autoregressive Joint Multiple Intent Detection and Slot Filling

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## Abstract

With the rise of non-autoregressive approach, some non-autoregressive models for joint multiple intent detection and slot filling have obtained the promising inference speed. However, most existing SLU models (1) suffer from the multi-modality problem that leads to reference intents and slots may not be suitable for training; (2) lack of alignment between the correct predictions of the two tasks, which extremely limits the overall accuracy. Therefore, in this paper, we propose **Modifying the Reference via Reinforcement Learning (MRRL)**, a novel method for multiple intent detection and slot filling, which introduces a modifier module and employs reinforcement learning. Specifically, we try to provide the better training target for the non-autoregressive SLU model via modifying the reference based on the output of the non-autoregressive SLU model, and propose a suitability reward to ensure that the output of the modifier module could fit well with the output of the non-autoregressive SLU model and does not deviate too far from the reference. In addition, we also propose a compromise reward to realize a flexible trade-off between the two subtasks. Experiments on two multi-intent datasets and non-autoregressive baselines demonstrate that our MRRL could consistently improve the performance of baselines. More encouragingly, our best variant achieves new state-of-the-art results, outperforming the previous best approach by 3.6 overall accuracy on MixATIS dataset.

## 1 Introduction

As a crucial task in dialogue systems, spoken language understanding (SLU) aims to understand the user’s current goal through constructing semantic frames (Tur and De Mori, 2011; Young et al., 2013; Zhu et al., 2023b; He and Garner, 2023b). Intent detection and slot filling are two common subtasks of SLU, where intent detection is an utterance-level

classification task and slot filling could be regarded as a sequence labeling task (He and Garner, 2023a; Cheng et al., 2023a).

However, an utterance often contains more than a just single intent in the real scenarios (Zhu et al., 2023a; Xing and Tsang, 2023; Cheng et al., 2023f). With this in mind, multi-intent SLU has received more and more attention (Xu and Sarikaya, 2013; Kim et al., 2017; Shet et al., 2019). Gangadharaiyah and Narayanaswamy (2019) proposes a multi-task framework to jointly model intent detection and slot filling. Qin et al. (2020) introduces graph attention networks (GAT) (Velickovic et al., 2018) to develop a fine-grained multi-intent prediction framework called AGIF, which aims to incorporate intent information into the slot filling decoding process in an adaptive manner. Qin et al. (2021b) proposes a novel global-locally graph interaction network GL-GIN, which applies the non-autoregressive modeling techniques to parallelize the decoding process, resulting in significant speedup compared to the traditional autoregressive SLU models. Xing and Tsang (2022a) further designs a two-stage SLU framework and achieves the mutual guidance between intent and slot, which enhances the overall accuracy of SLU. Song et al. (2022) explores attention mechanisms to extract the relevant information from the independent utterance contexts and capture shared label-specific features across all utterances in the training set. Xing and Tsang (2022b) proposes ReLa-Net, which utilizes a heterogeneous label graph to represent the statistical dependencies and hierarchies. Cheng et al. (2023d) applies contrastive learning to explore and leverage the inherent relationships in multi-intent SLU. Cheng et al. (2023a) proposes a scope-sensitive SLU model SS-RAN to reduce the distraction of the out-of-scope tokens and mitigate the error propagation problem caused by the bidirectional interaction.

Though existing non-autoregressive multi-intent SLU models have made the promising progress, we

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Tokens	Possibility	Reference
new	intent:atis_quantity, atis_flight slot: B-fromloc.city_name	atis_distance, atis_day_name B-city_name
guardia	intent:atis_airport, atis_airline slot: B-fromloc.airport_name	atis_distance, atis_day_name I-airport_name
downtown	intent: atis_city, atis_airfare slot: B-city_name	atis_distance, atis_day_name O

Table 1: The examples of the multi-modality problem. The gold intent label of the utterance is utilized as the intent of each token in the utterance.

find that most of them still face two issues:

(1) **Suffer from the multi-modality problem.**

Although non-autoregressive models have proven the effectiveness in terms of high inference speed, they still suffer from the multi-modality problem, which has been pointed out in several prior works in other tasks (Ran et al., 2020; Zhang et al., 2022a). However, this serious problem is still ignored in non-autoregressive SLU task. As shown in Table 1, for each token, there may be multiple possible correct slots. Besides, due to the widespread use of the token-level intent detection decoder, this problem also occurs in intent detection. Despite the utilization of GAT (Velickovic et al., 2018), these models still have little prior knowledge about the reference during the inference progress, which leads to some errors not commonly seen in autoregressive SLU models. For example, an I- slot might erroneously appear before its corresponding B- slot in the slot sequence output by a non-autoregressive model. As a result, the original reference intents and slots are not very suitable for model training.

(2) **Lack of the alignment between the correct predictions of the two subtasks.** Most of existing SLU models decode the hidden stats of the two subtasks independently without leveraging the correlations between them, which leads to the misalignment of the correct predictions of the two subtasks. As shown in Figure 1, the F1 score of slot filling and the accuracy of intent detection might increase or decrease asynchronously. Overall accuracy is an important metric and it denotes the ratio of the utterances for which both intents and slots are predicted correctly. Due to the lack of alignment, overall accuracy on utterance-level semantic frame parsing is much worse than these two subtasks, which is not conducive to deploying the SLU model in actual scenarios.

In this paper, we propose a novel model termed MRRL to tackle the above two issues, which introduces a modifier and applies reinforcement learn-

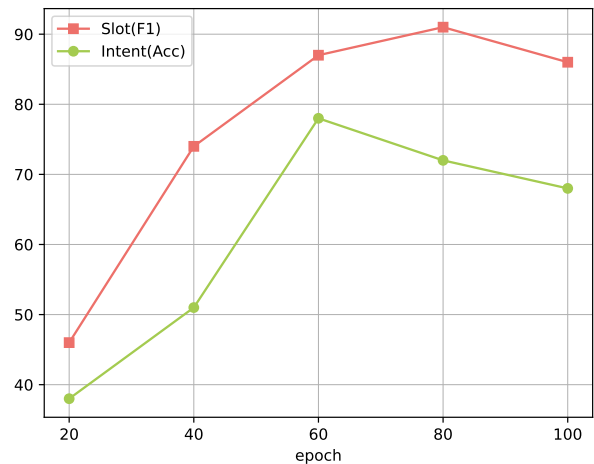


Figure 1: An example of the misalignment between the correct predictions of intent detection and slot filling. As the F1 score of slot filling (red) increases, the accuracy of intent detection (green) may decrease, which limits the overall accuracy of the utterance.

ing to provide a better training target for the non-autoregressive model. Since the reference intents and slots may not be suitable for training, we modify the reference intents and slots according to the output of the non-autoregressive SLU model. For the first problem, we propose a suitability reward to ensure that the output of the modifier fits well with the output of the non-autoregressive model and still maintain the original information. The first part of suitability reward is related to the training loss on the output of the modifier, and the second part is the similarity between the reference and the output of the modifier. For the second problem, we propose a compromise reward to improve the overall accuracy. We directly utilize the overall accuracy as the compromise reward to achieve a flexible trade-off between the accuracy of intent detection and the F1 score of slot filling. Experiment results show that MRRL consistently improves the performance of baselines on two benchmark datasets MixATIS and MixSNIPS (Hemphill et al., 1990; Coucke et al., 2018; Qin et al., 2020). Further analysis also verifies the advantages of our method.

The contributions of our work are three-fold:

- To the best of our knowledge, our work is the first attempt to employ reinforcement learning to solve the multi-modality problem and the misalignment problem in non-autoregressive multi-intent SLU models.
- We propose a novel method termed MRRL for non-autoregressive multi-intent SLU, which introduces a modifier and applies reinforce-

ment learning to modify the reference utterance into a form suitable for model training.

- Experimental results demonstrate that MRRL can efficiently improve the performance of the baselines and the best variant achieves the new state-of-the-art results.

## 2 Background

In this section, we first introduce the problem definition of the multi-intent SLU task and then introduce several multi-intent SLU models.

Given an input utterance  $\mathbf{x} = (x_1, x_2, \dots, x_n)$ , where  $n$  denotes the length of the utterance  $\mathbf{x}$ , multiple intent detection is a multi-label classification task and the token-level predicted intent sequence is denoted as  $\mathbf{y}^I = (y^{(1,I)}, y^{(2,I)}, \dots, y^{(n,I)})$ . The final utterance-level predicted intent sequence  $\mathbf{y}^I$  is obtained by the token-level intent voting strategy (Qin et al., 2021b; Xing and Tsang, 2022a). The reference intent sequence is denoted as  $\hat{\mathbf{y}}^I = (\hat{y}^{(1,I)}, \hat{y}^{(2,I)}, \dots, \hat{y}^{(m,I)})$ , where  $m$  denotes the number of intents in  $\mathbf{x}$ . Slot filling is a sequence labeling task (Qin et al., 2022; Cheng et al., 2023c; Zhu et al., 2023c). The predicted slot sequence is denoted as  $\mathbf{y}^S = (y^{(1,S)}, y^{(2,S)}, \dots, y^{(n,S)})$  and the reference slot sequence is denoted as  $\hat{\mathbf{y}}^S = (\hat{y}^{(1,S)}, \hat{y}^{(2,S)}, \dots, \hat{y}^{(n,S)})$ . For simplicity, we use  $\hat{\mathbf{y}}$  to denote the union of  $\hat{\mathbf{y}}^I$  and  $\hat{\mathbf{y}}^S$ .

### 2.1 Multi-Intent Spoken Language Understanding

Due to the interaction between the two subtasks of multiple intent detection and slot filling, joint models are widely used to consider the two tasks and update parameters. The multiple intent detection objective is defined as:

$$\text{CE}(\hat{y}, y) = \hat{y} \log(y) + (1 - \hat{y}) \log(1 - y) \quad (1)$$

$$\mathcal{L}_I = - \sum_{i=1}^n \sum_{j=1}^{N_I} \text{CE}(\hat{y}_i^{(j,I)}, y_i^{(j,I)}) \quad (2)$$

where  $N_I$  denotes the number of single intent labels,  $\hat{y}_i^{(j,I)}$  denotes the reference intent, and  $y_i^{(j,I)}$  denotes its corresponding predicted intent.

Similarly, the slot filling objective is defined as:

$$\mathcal{L}_S = - \sum_{i=1}^n \sum_{j=1}^{N_S} \hat{y}_i^{(j,S)} \log(y_i^{(j,S)}) \quad (3)$$

where  $N_S$  denotes the number of slot labels,  $\hat{y}_i^{(j,S)}$  denotes the reference slot, and  $y_i^{(j,S)}$  denotes its corresponding predicted slot.

The final joint objective is formulated as:

$$\mathcal{L} = \alpha \mathcal{L}_I + \beta \mathcal{L}_S \quad (4)$$

where  $\alpha$  and  $\beta$  are hyper-parameters.

### 2.2 AGIF

AGIF (Qin et al., 2020) is a token-level adaptive interaction network that implements fine-grained integration of multi-intent information. An intent-slot graph interaction layer is used to model the strong correlation between slots and intents. Such an interaction layer is applied adaptively to each token of an utterance, with the advantage that relevant intent information can be automatically extracted. Restricted by the autoregressive paradigm, during the inference, the previously predicted tokens must be fed to the decoder to generate the next token step by step, which leads to slower inference speed.

### 2.3 GL-GIN

GL-GIN (Qin et al., 2021b) is a global-locally graph-interaction network, including a local slot-aware graph layer and a global intent-slot interaction layer. Owing to the non-autoregressive architecture, GL-GIN achieves to generate intents and slots sequence simultaneously, thus increasing the inference speed. However, we find that it is not enough to just rely on the local graph interaction layer to model the slot dependencies, which limits the performance (see Sec.4.5 for more details).

### 2.4 Co-guiding Net

Co-guiding Net (Xing and Tsang, 2022a) is a two-stage framework that allows intent detection and slot filling to learn from each other. The first stage produces initial estimated labels for the two tasks and the second stage leverages estimated labels as prior label information. Two heterogeneous graph attention networks are proposed to work on the two aforementioned graphs for modeling the guidance between intent and slot.

### 2.5 ReLa-Net

ReLa-Net (Xing and Tsang, 2022b) improves joint multiple intent detection and slot filling from a new perspective, which exploits the label typologies and relations through a heterogeneous label graph and a recurrent heterogeneous label matching network. The heterogeneous label graph includes both the global statistical dependencies and slot label hierarchies, which is proposed to represent the statistical

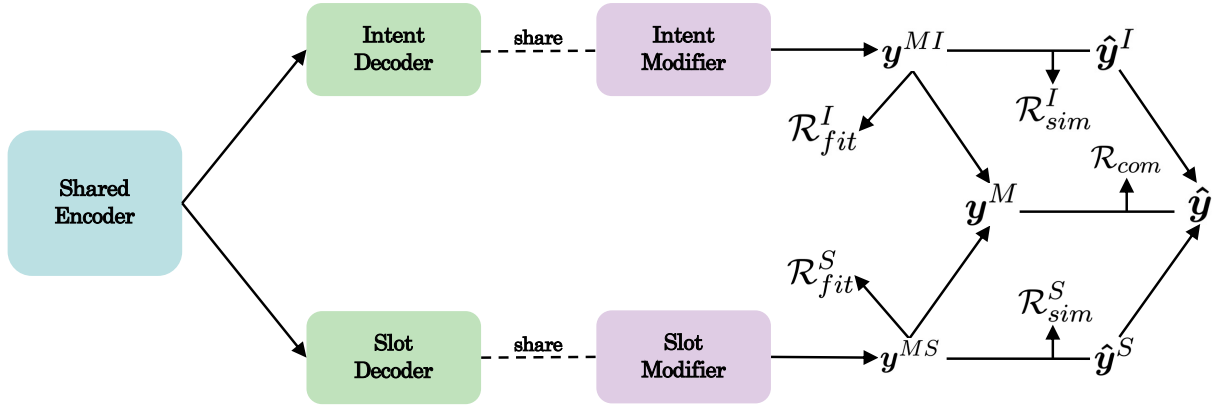


Figure 2: The main architecture of MRRL. Two modifiers are trained to optimize the suitability reward and the compromise reward, where suitability reward is the weighted sum of fit reward and similarity reward. Fit reward relates to the joint training loss of the modifiers and similarity reward relates to the similarity with the reference. Compromise reward is related to the overall accuracy.

dependencies and hierarchies in rich relations. And a recurrent heterogeneous label matching network is proposed to end-to-end capture the beneficial information from the heterogeneous label graph and use them for tackling the joint task.

### 3 Approach

In this section, we first present the overview of our model (§3.1), which introduces the modifier module including an intent modifier and a slot modifier into the original architecture. Then, we introduce the pretrain-finetune paradigm (§3.2), where pre-training could establish a better initial state for the fine-tuning of the modifier module. Finally, we introduce the reinforcement learning module, which is applied to make the output of the modifier more suitable for model training (§3.3). Figure 2 illustrates the overview of our proposed method.

#### 3.1 Model Overview

To alleviate the problem of multi-modality and misalignment, in addition to the conventional encoder-decoder architecture, we introduce a modifier module including an intent modifier and a slot modifier to modify the reference according to the output of the non-autoregressive model. Note that the modifier module only affects the training stage, so the inference cost does not change.

The modifier module is designed as a key component capable of transforming the reference into a more suitable form for training. The transformation process takes into account both the reference itself and the output generated by the non-autoregressive model. Through leveraging this dual information,

the modifier module has the potential to optimize the reference, making it more aligned with the training objectives and enhancing the overall training process. Thus, we utilize two non-autoregressive decoders as the architecture of the modifier module. Similarly, the token-level predicted intent sequence of the intent modifier is denoted as  $\mathbf{y}^{MI'} = (y^{(1,MI')}, y^{(2,MI')}, \dots, y^{(n,MI')})$ , the output of the intent modifier  $\mathbf{y}^{MI}$  is also obtained by the voting technique. The output of the slot modifier is denoted as  $\mathbf{y}^{MS} = (y^{(1,MS)}, y^{(2,MS)}, \dots, y^{(n,MS)})$ , and the union of  $\mathbf{y}^{MI}$  and  $\mathbf{y}^{MS}$  is denoted as  $\mathbf{y}^M$ . We use  $P_M$  to denote the probability distribution of the modifier module:

$$P_M(\mathbf{y}^{MI'}, \mathbf{y}^{MS} | \mathbf{x}, \hat{\mathbf{y}}) = \prod_{i=1}^n p_M(y^{(i,MI')}, y^{(i,MS)} | \mathbf{x}, \hat{\mathbf{y}}), \quad (5)$$

Diverging from conventional SLU models, the non-autoregressive SLU model is trained with the output of the modifier module  $\mathbf{y}^{MI}$  and  $\mathbf{y}^{MS}$  rather than the original reference  $\hat{\mathbf{y}}^I$  and  $\hat{\mathbf{y}}^S$ . Then the multiple intent detection objective  $\mathcal{L}_{MI}$  and slot filling objective  $\mathcal{L}_{MS}$  are formulated as:

$$\mathcal{L}_{MI} = - \sum_{i=1}^n \sum_{j=1}^{N_I} \text{CE}(\hat{y}_i^{(j,I)}, y_i^{(j,MI)}) \quad (6)$$

$$\mathcal{L}_{MS} = - \sum_{i=1}^n \sum_{j=1}^{N_S} \hat{y}_i^{(j,S)} \log(y_i^{(j,MS)}) \quad (7)$$

where  $y_i^{(j,MI)}$  denotes the predicted intent of the intent modifier and  $y_i^{(j,MS)}$  denotes the predicted slot

of the slot modifier. Then the final joint objective of the modifier module  $\mathcal{L}_M$  is defined as:

$$\mathcal{L}_M = \alpha\mathcal{L}_{MI} + \beta\mathcal{L}_{MS} \quad (8)$$

### 3.2 Pretrain-Finetune Paradigm

When directly applying reinforcement learning to train the modifier, a common problem arises where the modifier become trapped in a non-optimal state, resulting in the generation of sequences with meaningless intents and slots. The issue is inherent to reinforcement learning due to its sensitivity to initial states (Mihatsch and Neuneier, 2002; Fei et al., 2020; Shao et al., 2023).

To address this challenge, we utilize a pretrain-finetune paradigm. During the pre-training phase, we employ a joint objective  $\mathcal{L}$  as defined in Eq.4 to establish a better initial state for the modifier. This pre-training strategy aims to provide the modifier with a more favorable starting point, making subsequent fine-tuning easier and reducing the likelihood of falling into local optimization.

Following the pre-training phase, we proceed to fine-tune the modifier using reinforcement learning, incorporating suitability reward and compromise reward to further guide the learning process. This fine-tuning approach enables the designed modifier to refine its behavior and adjust its outputs based on the reinforcement signals received.

### 3.3 Reinforcement Learning

The primary objective of the modifier module is to generate a training target which is better suited for non-autoregressive models. Motivated by Wu et al. (2018); Rao et al. (2021); Lu et al. (2022); Shao et al. (2023), we quantify the requirements for the modifier module into two reward functions and optimize them via reinforcement learning. The level of appropriateness of this target could be quantified using two reward functions.

Firstly, it is crucial for the output of the modifier module to align closely with the output of the SLU model. We employ a fitting reward  $\mathcal{R}_{fit}$  that shares a formal resemblance to the loss function  $\mathcal{L}_M$ , aiming to incentivize the reduction of the training loss.

For the output of the intent modifier  $\mathbf{y}^{MI}$  and the output of the slot modifier  $\mathbf{y}^{MS}$ , we apply the length normalization to keep the scale of reward stable and combine the normalized  $\mathcal{L}_{MI}$  and  $\mathcal{L}_{MS}$  to obtain the intent fit reward  $R_{fit}^I$ , the slot fit reward

$R_{fit}^S$  and the final fit reward  $R_{fit}$ :

$$\mathcal{R}_{fit}^I = -\frac{1}{m}\mathcal{L}_{MI} \quad (9)$$

$$\mathcal{R}_{fit}^S = -\frac{1}{n}\mathcal{L}_{MS} \quad (10)$$

$$\mathcal{R}_{fit} = \alpha\mathcal{R}_{fit}^I + \beta\mathcal{R}_{fit}^S \quad (11)$$

where  $m$  is the length of the output of the intent modifier  $\mathbf{y}^{MI}$  and  $n$  is the length of the output of the slot modifier  $\mathbf{y}^{MS}$ .

Secondly, the output of the modifier should not deviate too far from the reference, so we utilize a similarity reward  $\mathcal{R}_{sim}$  to measure the similarity between the reference and the output of the modifier module. We use the accuracy of multiple intent detection and F1 score of slot filling as the similarity function to measure the similarity between  $\mathbf{y}_1$  and  $\mathbf{y}_2$ , which are denoted as  $\mathcal{S}_I(\mathbf{y}_1, \mathbf{y}_2)$  and  $\mathcal{S}_S(\mathbf{y}_1, \mathbf{y}_2)$ , respectively. Then the intent similarity reward  $\mathcal{R}_{sim}^I$ , the slot similarity reward  $\mathcal{R}_{sim}^S$  and the final similarity reward  $R_{sim}$  are formulated as:

$$\mathcal{R}_{sim}^I = \mathcal{S}_I(\hat{\mathbf{y}}^I, \mathbf{y}^{MI}) \quad (12)$$

$$\mathcal{R}_{sim}^S = \mathcal{S}_S(\hat{\mathbf{y}}^S, \mathbf{y}^{MS}) \quad (13)$$

$$\mathcal{R}_{sim} = \alpha\mathcal{R}_{sim}^I + \beta\mathcal{R}_{sim}^S \quad (14)$$

where  $\hat{\mathbf{y}}^I$  is the reference intent and  $\hat{\mathbf{y}}^S$  is the reference slot. The suitability reward  $\mathcal{R}_{suit}$  is the weighted sum of  $\mathcal{R}_{fit}$  and  $\mathcal{R}_{sim}$ :

$$\mathcal{R}_{suit} = \lambda_f\mathcal{R}_{fit} + \lambda_s\mathcal{R}_{sim} \quad (15)$$

where  $\lambda_f$  and  $\lambda_s$  are two hyper-parameters.

Another common problem in many multi-intent SLU models is that the F1 score of slot filling and the accuracy of intent detection might increase or decrease asynchronously. As the F1 score of slot filling increases, the accuracy of intent detection might begin to decrease. Overall accuracy denotes the ratio of utterances whose intents and slots are all correctly predicted. As a result, it is crucial to achieve a trade-off between the accuracy of intent detection and the F1 score of slot filling.

Intuitively, we apply the overall accuracy to measure the similarity between  $\mathbf{y}_1$  and  $\mathbf{y}_2$ , and denote it as  $\mathcal{S}_A(\mathbf{y}_1, \mathbf{y}_2)$ . We directly apply  $\mathcal{S}_A$  as the compromise reward  $\mathcal{R}_{com}$  to improve the overall accuracy. The compromise reward  $\mathcal{R}_{com}$  is:

$$\mathcal{R}_{com} = \mathcal{S}_A(\hat{\mathbf{y}}, \mathbf{y}^M) \quad (16)$$

The final reward  $\mathcal{R}$  for the modifier module is:

$$\mathcal{R} = \mathcal{R}_{suit} + \lambda_c\mathcal{R}_{com} \quad (17)$$

Model	MixATIS			MixSNIPS		
	Overall(Acc)	Slot(F1)	Intent(Acc)	Overall(Acc)	Slot(F1)	Intent(Acc)
Attention BiRNN (Liu and Lane, 2016)	39.1	86.4	74.6	59.5	89.4	95.4
Slot-Gated (Goo et al., 2018)	35.5	87.7	63.9	55.4	87.9	94.6
Bi-Model (Wang et al., 2018b)	34.4	83.9	70.3	63.4	90.7	95.6
SF-ID (E et al., 2019)	34.9	87.4	66.2	59.9	90.6	95.0
Stack-Propagation (Qin et al., 2019)	40.1	87.8	72.1	72.9	94.2	96.0
AGIF (Qin et al., 2020)	40.8	86.7	74.4	74.2	94.2	95.1
LR-Transformer (Cheng et al., 2021b,a)	43.3	88.0	76.1	74.9	94.4	96.6
GISCo (Song et al., 2022)	48.2	88.5	75.0	75.9	95.0	95.5
SSRAN (Cheng et al., 2023a)	48.9	89.4	77.9	77.5	95.8	98.4
GL-GIN (Qin et al., 2021b)	43.0	88.2	76.3	73.7	94.0	95.7
w/ MRRL	47.2 <sup>†</sup>	88.7 <sup>†</sup>	78.4 <sup>†</sup>	75.8 <sup>†</sup>	95.2 <sup>†</sup>	96.5 <sup>†</sup>
Co-guiding Net (Xing and Tsang, 2022a)	51.3	89.8	79.1	77.5	95.1	97.7
w/ MRRL	54.8 <sup>†</sup>	90.6 <sup>†</sup>	79.5 <sup>†</sup>	79.0 <sup>†</sup>	96.4 <sup>†</sup>	98.6 <sup>†</sup>
ReLa-Net (Xing and Tsang, 2022b)	52.2	90.1	78.5	76.1	94.7	97.6
w/ MRRL	55.8 <sup>†</sup>	92.4 <sup>†</sup>	79.8 <sup>†</sup>	79.3 <sup>†</sup>	96.8 <sup>†</sup>	99.1 <sup>†</sup>

Table 2: Results comparison. † denotes our model significantly outperforms baselines with  $p < 0.01$  under t-test.

where  $\lambda_c$  is a hyper-parameter. We utilize the RE-INFORCE algorithm (Williams, 1992; Zhang et al., 2021) to optimize the reward  $\mathcal{R}$ :

$$\begin{aligned} \nabla \mathcal{J} &= \nabla \sum_{\mathbf{y}^M} P_M(\mathbf{y}^{MI'}, \mathbf{y}^{MS} | \mathbf{x}, \hat{\mathbf{y}}) \mathcal{R} \\ &= \mathbb{E}_{\mathbf{y}^M \sim P_M} [\nabla \log P_M(\mathbf{y}^{MI'}, \mathbf{y}^{MS} | \mathbf{x}, \hat{\mathbf{y}}) \mathcal{R}] \end{aligned} \quad (18)$$

## 4 Experiments

### 4.1 Datasets and Metrics

We conduct our experiments on two public multi-intent datasets<sup>1</sup>: cleaned version of MixATIS and MixSNIPS (Qin et al., 2020). MixATIS dataset is collected from ATIS dataset (Hemphill et al., 1990) and MixSNIPS dataset is collected from SNIPS dataset (Coucke et al., 2018). MixATIS includes 13,162 utterances for training, 756 utterances for validation and 828 utterances for testing. MixSNIPS includes 39,776 utterances for training, 2,198 utterances for validation and 2,199 utterances for testing. Compared to single-domain MixATIS dataset, MixSNIPS dataset is more complicated because of the intent diversity and large vocabulary.

Following Goo et al. (2018); Qin et al. (2021b), we evaluate accuracy (Acc) for multiple intent detection, F1 score for slot filling, and overall accuracy for the utterance-level semantic frame parsing. Overall accuracy denotes the ratio of the utterances whose intents and slots are all correctly predicted.

### 4.2 Implementation Details

We pre-train the model for 5K steps with a batch size 16 on each dataset. During both pre-training

<sup>1</sup><https://github.com/LooperXX/AGIF>

and fine-tuning, we use Adam optimizer (Kingma and Ba, 2015) with  $\beta_1 = 0.9$ ,  $\beta_2 = 0.98$ , and 4k warm-up updates to optimize 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.  $\alpha$  is set to 0.9,  $\beta$  is set to 0.1,  $\lambda_f$  is set to 0.3,  $\lambda_s$  is set to 0.2, and  $\lambda_c$  is set to 0.5. All parameters are obtained by the annealing strategy (Ahn et al., 2019). Experiments are conducted at GeForce RTX 2080Ti and TITAN Xp.

### 4.3 Main Results

We introduce MRRL to many baselines. The results on the test sets is listed in Table 2, from which we have the following observations:

(1) Our MRRL consistently improves the performance of several baselines on all tasks and datasets. More encouragingly, our best variant (i.e. *ReLa-Net w/ MRRL*) achieves new state-of-the-art results. Specifically speaking, on MixATIS dataset, it overpasses the previous state-of-the-art model ReLa-Net by 3.6 and 2.3 on overall accuracy and slot filling, and overpasses the previous state-of-the-art model Co-guiding Net by 0.7 on multiple intent detection; on MixSNIPS dataset, it overpasses SSRAN by 1.8, 1.0 and 0.7 on utterance-level semantic frame parsing, slot filling and multiple intent detection, respectively. This is because our methods provide a better training target for the non-autoregressive model by modifying the reference, which might be not be suitable for training due to the multi-modality problem.

(2) It is worth noting that the improvement on the MixATIS dataset is more obvious than that on

Model	MixATIS			MixSNIPS		
	Overall(Acc)	Slot(F1)	Intent(Acc)	Overall(Acc)	Slot(F1)	Intent(Acc)
ReLa-Net w/ MRRL	<b>55.8</b>	<b>92.4</b>	<b>79.8</b>	<b>79.3</b>	<b>96.8</b>	<b>99.1</b>
w/o $\mathcal{R}_{suit}$	53.6 ( $\downarrow$ 1.8)	91.3 ( $\downarrow$ 1.1)	78.8 ( $\downarrow$ 1.0)	78.1 ( $\downarrow$ 1.2)	95.3 ( $\downarrow$ 1.5)	98.2 ( $\downarrow$ 0.9)
w/o $\mathcal{R}_{fit}$	54.4 ( $\downarrow$ 1.4)	91.6 ( $\downarrow$ 0.8)	79.2 ( $\downarrow$ 0.6)	78.4 ( $\downarrow$ 0.9)	95.6 ( $\downarrow$ 1.2)	98.5 ( $\downarrow$ 0.6)
w/o $\mathcal{R}_{sim}$	54.2 ( $\downarrow$ 1.6)	91.8 ( $\downarrow$ 0.6)	79.4 ( $\downarrow$ 0.4)	78.6 ( $\downarrow$ 0.7)	95.8 ( $\downarrow$ 1.0)	98.7 ( $\downarrow$ 0.4)
w/o $\mathcal{R}_{com}$	53.0 ( $\downarrow$ 2.8)	92.0 ( $\downarrow$ 0.4)	79.5 ( $\downarrow$ 0.3)	77.2 ( $\downarrow$ 2.1)	96.5 ( $\downarrow$ 0.3)	98.8 ( $\downarrow$ 0.3)
w/o $\mathcal{R}_{suit}$ + More Parameters	53.8 ( $\downarrow$ 2.0)	91.4 ( $\downarrow$ 1.0)	79.2 ( $\downarrow$ 0.6)	78.5 ( $\downarrow$ 0.8)	95.7 ( $\downarrow$ 1.1)	98.4 ( $\downarrow$ 0.7)
w/o $\mathcal{R}_{com}$ + More Parameters	53.4 ( $\downarrow$ 2.4)	92.2 ( $\downarrow$ 0.2)	79.6 ( $\downarrow$ 0.2)	78.8 ( $\downarrow$ 0.5)	96.6 ( $\downarrow$ 0.2)	98.9 ( $\downarrow$ 0.2)

Table 3: Results of ablation experiments of ReLa-Net on MixATIS dataset and MixSNIPS dataset.

the MixSNIPS dataset. We suspect that this is because MixSNIPS dataset is more complicated than MixATIS dataset. MixATIS dataset has a smaller vocabulary and fewer kinds of intentions and slots, where it is easier to propose a more suitable training target for non-autoregressive multi-intent models. As a result, the gain is greater on MixATIS dataset.

(3) The improvements in terms of overall accuracy are much sharper. This is because our method includes the compromise reward to overcome the misalignment problem. In this way, the correct predictions of the two tasks can be better aligned. As a result, more test samples get the correct utterance-level semantic frame parsing results, and then the overall accuracy is improved more significantly.

#### 4.4 Analysis

We conduct a set of ablation experiments on ReLa-Net w/ MRRL to verify the advantages of MRRL from different perspectives, and the experimental results are shown in Table 3.

##### 4.4.1 Effectiveness of Suitability Reward

Suitability reward is one of the key contributions of our MRRL, which is dedicated to solving the problem of unsuitability of the reference caused by the multi-modality problem. To verify this, we remove the suitability reward and refer it to *w/o  $\mathcal{R}_{suit}$*  in Table 3. We can clearly observe that overall accuracy drops by 1.8 on MixATIS and 1.2 on MixSNIPS, the slot F1 drops by 1.1 on MixATIS and 1.5 on MixSNIPS, and intent accuracy drops by 1.0 on MixATIS and 0.9 on MixSNIPS. When we only remove a component of  $\mathcal{R}_{suit}$  (i.e. *w/o  $\mathcal{R}_{fit}$*  and *w/o  $\mathcal{R}_{sim}$* ), the performance also degrades in varying degrees. Following previous works (Qin et al., 2020, 2021b), to verify that the proposed suitability reward rather than the added parameters works, we increase the layers of intent decoder and slot decoder when  $\mathcal{R}_{suit}$  is removed and refer it to *w/o  $\mathcal{R}_{suit}$  + More Parameters*. We could observe that despite the added parameters, it still performs

worse than *ReLa-Net w/ MRRL*, which suggests that the improvements come from the proposed suitability reward rather than involved parameters.

##### 4.4.2 Effectiveness of Compromise Reward

To verify the effectiveness of compromise reward, we remove it and refer it to *w/o  $\mathcal{R}_{com}$* . We can find that the performance is decreased on all tasks and datasets. Moreover, the drop in overall accuracy is more pronounced than that of slot F1 and intent accuracy on the two datasets, which suggests that compromise reward can efficiently improve the overall accuracy. It is worth noting that slot F1 and intent accuracy do not drop when compromise reward is introduced. We believe that the reason is that compromise reward can further achieve the mutual guidance between intent and slot indirectly when realizing the flexible trade-off between the two subtasks. Like Sec.4.4.1, we also increase the layers of intent decoder and slot decoder to verify that the compromise reward rather than the added parameters works, which is named as *w/o  $\mathcal{R}_{com}$  + More Parameters*. The result also suggests that the improvements come from the compromise reward.

#### 4.5 Case Study

To further demonstrate how our approach alleviates the multi-modality problem, we provide several cases generated from GL-GIN, ReLa-Net and ReLa-Net + MRRL in Figure 3.

It is obvious that despite the utilization of GAT, GL-GIN is still impacted by multi-modality issue, where B-airport\_name is incorrectly predicted as B-fromloc.airport\_name. We believe this is because GL-GIN has little prior knowledge about the reference during the inference progress, so *milwaukee* is incorrectly predicted as the departure place when there is no destination in the utterance. Compared to GL-GIN, ReLa-Net performs a little better, where the predicted intent is right but there are still some mistakes in the predicted slots. When MRRL is introduced to ReLa-Net, the prediction is abso-

## Models

	Utterance:	what	ground	transportation	is	available	between	milwaukee	airport	and
Ref.	Slot:	O	O	O	O	O	O	B-airport_name	I-airport_name	O
	Intent:	atis_ground_service								
GL-GIN	Slot:	O	O	O	O	O	O	B-fromloc.airport_name	I-fromloc.airport_name	O
	Intent:	atis_distance								
ReLa-Net	Slot:	O	O	O	O	O	O	B-fromloc.airport_name	I-fromloc.airport_name	O
	Intent:	atis_ground_service								
ReLa-Net + MRRL	Slot:	O	O	O	O	O	O	B-airport_name	I-airport_name	O
	Intent:	atis_ground_service								

Figure 3: Cases that generated from GL-GIN (Qin et al., 2021b), ReLa-Net (Xing and Tsang, 2022b) and ReLa-Net w/ MRRL. The red text indicates the incorrect predictions.

lutely right, which indicates that MRRL can indeed alleviate the multi-modality problem.

## 5 Related Work

### 5.1 Intent Detection and Slot Filling

As deep learning obtains impressive performance on various tasks (Li et al., 2021, 2022; Zhang et al., 2022b; Yu et al., 2023; Zhang et al., 2023b; Li et al., 2023; Zhang et al., 2023a), more and more studies utilize deep learning to SLU and achieve notable achievements (Hakkani-Tür et al., 2016; Xia et al., 2018; Liu et al., 2019; Huang et al., 2020; Wu et al., 2020; Qin et al., 2021a,b; Huang et al., 2021, 2022; Chen et al., 2022a,b; Cheng et al., 2023e,b). Recently, the multi-intent SLU problem has garnered the significant attention, leading to the emergence of several graph-based models which have demonstrated promising results. AGIF (Qin et al., 2020) applies graph attention to directly connect the slot nodes of each token with all predicted intent nodes. GL-GIN (Qin et al., 2021b) further introduces a global-local graph interaction network specifically and leverages graph-based techniques to capture interactions between different parts of the input utterance. More recently, Xing and Tsang (2022a) proposes Co-guiding Net to enhance the overall performance via enabling slot and intent to guide and influence each other during the training process. Xing and Tsang (2022b) proposes ReLa-Net to further exploit label typologies and relations.

However, most of the previous models neglect the multi-modality problem and the misalignment problem, which are both detrimental to the perfor-

mance of the SLU model. Therefore, we introduce a modifier and propose a suitability reward to overcome the multi-modality problem and a compromise reward to overcome the misalignment problem and improve the overall accuracy.

### 5.2 Reinforcement Learning

Several NLP tasks have been solved through reinforcement learning techniques, such as dialogue generation (Li et al., 2016, 2017), question answering (Xiong et al., 2018; Lu et al., 2022), machine translation (Wu et al., 2018; Shao et al., 2023), sentiment transfer (Xu et al., 2018), and essay scoring (Wang et al., 2018c). In SLU task, Wang et al. (2018a) applies reinforcement learning to learn the wrong labeled slots with or without user’s feedback, Rao et al. (2021) proposes a reinforce framework to enhance automatic speech recognition robustness in SLU. In our work, we apply reinforcement learning to alleviate the multi-modality problem and the misalignment problem in non-autoregressive SLU.

## 6 Conclusion

In this paper, we propose MRRL, a simple yet effective method to alleviate the multi-modality problem and misalignment problem in non-autoregressive multi-intent SLU. We introduce a modifier to provide a more suitable training target for the model, and apply reinforcement learning with the suitability reward and compromise reward. Experiments and analysis demonstrate the effectiveness of our proposed method, which can consistently improve the performance of baselines and the best variant achieves new state-of-the-art performance. Future



work will focus on how to further alleviate the two problems for non-autoregressive multi-intent SLU.

## Limitations

Although our MRRL consistently improve the performance of the baselines, and the best variant (i.e. ReLa-Net + MRRL) achieves new state-of-the-art results, it does not change the inherent structure of the model. In fact, the BiLSTM used is relatively simple, which limits the performance of SLU. In the future, we will pay more attention to these deficiencies and try to design better frameworks for non-autoregressive multi-intent SLU.

## Acknowledgements

We thank all anonymous reviewers for their constructive comments. This paper was partially supported by Shenzhen Science & Technology Research Program (No: GXWD20201231165807007-20200814115301001) and NSFC (No: 62176008).

## References

- Byung Hoon Ahn, Prannoy Pilligundla, and Hadi Esmaeilzadeh. 2019. Reinforcement learning and adaptive sampling for optimized dnn compilation. *ArXiv preprint*.
- Dongsheng Chen, Zhiqi Huang, Xian Wu, Shen Ge, and Yuexian Zou. 2022a. Towards joint intent detection and slot filling via higher-order attention. In *Proc. of IJCAI*.
- Dongsheng Chen, Zhiqi Huang, and Yuexian Zou. 2022b. Leveraging bilinear attention to improve spoken language understanding. In *Proc. of ICASSP*.
- Lizhi Cheng, Weijia Jia, and Wenmian Yang. 2021a. An effective non-autoregressive model for spoken language understanding. In *Proc. of CIKM*.
- Lizhi Cheng, Wenmian Yang, and Weijia Jia. 2021b. A result based portable framework for spoken language understanding. In *Proc. of ICME*.
- Lizhi Cheng, Wenmian Yang, and Weijia Jia. 2023a. A scope sensitive and result attentive model for multi-intent spoken language understanding. In *Proc. of AAAI*.
- Xuxin Cheng, Bowen Cao, Qichen Ye, Zhihong Zhu, Hongxiang Li, and Yuexian Zou. 2023b. MI-lmcl: Mutual learning and large-margin contrastive learning for improving asr robustness in spoken language understanding. In *Proc. of ACL Findings*.
- Xuxin Cheng, Wanshi Xu, Ziyu Yao, Zhihong Zhu, Yaowei Li, Hongxiang Li, and Yuexian Zou. 2023c. FC-MTLF: A Fine- and Coarse-grained Multi-Task Learning Framework for Cross-Lingual Spoken Language Understanding. In *Proc. of Interspeech*.
- Xuxin Cheng, Wanshi Xu, Zhihong Zhu, Hongxiang Li, and Yuexian Zou. 2023d. Towards spoken language understanding via multi-level multi-grained contrastive learning. In *Proc. of CIKM*.
- Xuxin Cheng, Ziyu Yao, Zhihong Zhu, Yaowei Li, Hongxiang Li, and Yuexian Zou. 2023e. C 2 A-SLU: Cross and Contrastive Attention for Improving ASR Robustness in Spoken Language Understanding. In *Proc. of Interspeech*.
- Xuxin Cheng, Zhihong Zhu, Wanshi Xu, Yaowei Li, Hongxiang Li, and Yuexian Zou. 2023f. Accelerating multiple intent detection and slot filling via targeted knowledge distillation. In *Proc. of EMNLP Findings*.
- Alice Coucke, Alaa Saade, Adrien Ball, Théodore Bluche, Alexandre Caulier, David Leroy, Clément Doumouro, Thibault Gisselbrecht, Francesco Caltagirone, Thibaut Lavril, et al. 2018. Snips voice platform: an embedded spoken language understanding system for private-by-design voice interfaces. *ArXiv preprint*.
- Haihong E, Peiqing Niu, Zhongfu Chen, and Meina Song. 2019. A novel bi-directional interrelated model for joint intent detection and slot filling. In *Proc. of ACL*.
- Yingjie Fei, Zhuoran Yang, Yudong Chen, Zhaoran Wang, and Qiaomin Xie. 2020. Risk-sensitive reinforcement learning: Near-optimal risk-sample trade-off in regret. In *Proc. of NeurIPS*.
- Rashmi Gangadharaiah and Balakrishnan Narayanaswamy. 2019. Joint multiple intent detection and slot labeling for goal-oriented dialog. In *Proc. of NAACL*.
- Chih-Wen Goo, Guang Gao, Yun-Kai Hsu, Chih-Li Huo, Tsung-Chieh Chen, Keng-Wei Hsu, and Yun-Nung Chen. 2018. Slot-gated modeling for joint slot filling and intent prediction. In *Proc. of NAACL*.
- Dilek Hakkani-Tür, Gökhan Tür, Asli Celikyilmaz, Yun-Nung Chen, Jianfeng Gao, Li Deng, and Ye-Yi Wang. 2016. Multi-domain joint semantic frame parsing using bi-directional RNN-LSTM. In *Proc. of INTERSPEECH*.
- Mutian He and Philip N. Garner. 2023a. Can ChatGPT Detect Intent? Evaluating Large Language Models for Spoken Language Understanding. In *Proc. of Interspeech*.
- Mutian He and Philip N Garner. 2023b. The interpreter understands your meaning: End-to-end spoken language understanding aided by speech translation. *ArXiv preprint*.
- Charles T. Hemphill, John J. Godfrey, and George R. Doddington. 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.*
- Zhiqi Huang, Fenglin Liu, Peilin Zhou, and Yuexian Zou. 2021. Sentiment injected iteratively co-interactive network for spoken language understanding. In *Proc. of ICASSP*.
- Zhiqi Huang, Fenglin Liu, and Yuexian Zou. 2020. Federated learning for spoken language understanding. In *Proc. of COLING*.
- Zhiqi Huang, Milind Rao, Anirudh Raju, Zhe Zhang, Bach Bui, and Chul Lee. 2022. MTL-SLT: Multi-task learning for spoken language tasks. In *Proceedings of the 4th Workshop on NLP for Conversational AI*.
- Byeongchang Kim, Seonghan Ryu, and Gary Geunbae Lee. 2017. Two-stage multi-intent detection for spoken language understanding. *Multimedia Tools and Applications*.
- Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In *Proc. of ICLR*.
- Jinpeng Li, Yingce Xia, Rui Yan, Hongda Sun, Dongyan Zhao, and Tie-Yan Liu. 2021. Stylized dialogue generation with multi-pass dual learning. In *Proc. of NeurIPS*.
- Jiwei Li, Will Monroe, Alan Ritter, Dan Jurafsky, Michel Galley, and Jianfeng Gao. 2016. Deep reinforcement learning for dialogue generation. In *Proc. of EMNLP*.
- Jiwei Li, Will Monroe, Tianlin Shi, Sébastien Jean, Alan Ritter, and Dan Jurafsky. 2017. Adversarial learning for neural dialogue generation. In *Proc. of EMNLP*.
- Yinghui Li, Haojing Huang, Shirong Ma, Yong Jiang, Yangning Li, Feng Zhou, Hai-Tao Zheng, and Qingyu Zhou. 2023. On the (in)effectiveness of large language models for chinese text correction. *ArXiv preprint*.
- Yinghui Li, Shirong Ma, Qingyu Zhou, Zhongli Li, Li Yangning, Shulin Huang, Ruiyang Liu, Chao Li, Yunbo Cao, and Haitao Zheng. 2022. Learning from the dictionary: Heterogeneous knowledge guided fine-tuning for Chinese spell checking. In *Proc. of EMNLP Findings*.
- Bing Liu and Ian R. Lane. 2016. Attention-based recurrent neural network models for joint intent detection and slot filling. In *Proc. of INTERSPEECH*.
- Yijin Liu, Fandong Meng, Jinchao Zhang, Jie Zhou, Yufeng Chen, and Jinan Xu. 2019. CM-net: A novel collaborative memory network for spoken language understanding. In *Proc. of EMNLP*.
- Jiaying Lu, Xin Ye, Yi Ren, and Yezhou Yang. 2022. Good, better, best: Textual distractors generation for multiple-choice visual question answering via reinforcement learning. In *Proc. of CVPR*.
- Oliver Mihatsch and Ralph Neuneier. 2002. Risk-sensitive reinforcement learning. *Machine learning*.
- Libo Qin, Wanxiang Che, Yangming Li, Haoyang Wen, and Ting Liu. 2019. A stack-propagation framework with token-level intent detection for spoken language understanding. In *Proc. of EMNLP*.
- Libo Qin, Qiguang Chen, Tianbao Xie, Qixin Li, Jianguang Lou, Wanxiang Che, and Min-Yen Kan. 2022. GL-CLEF: A global-local contrastive learning framework for cross-lingual spoken language understanding. In *Proc. of ACL*.
- Libo Qin, Tailu Liu, Wanxiang Che, Bingbing Kang, Sendong Zhao, and Ting Liu. 2021a. A co-interactive transformer for joint slot filling and intent detection. In *Proc. of ICASSP*.
- Libo Qin, Fuxuan Wei, Tianbao Xie, Xiao Xu, Wanxiang Che, and Ting Liu. 2021b. GL-GIN: Fast and accurate non-autoregressive model for joint multiple intent detection and slot filling. In *Proc. of ACL*.
- Libo Qin, Xiao Xu, Wanxiang Che, and Ting Liu. 2020. AGIF: An adaptive graph-interactive framework for joint multiple intent detection and slot filling. In *Proc. of EMNLP Findings*.
- Qiu Ran, Yankai Lin, Peng Li, and Jie Zhou. 2020. Learning to recover from multi-modality errors for non-autoregressive neural machine translation. In *Proc. of ACL*.
- Milind Rao, Pranav Dheram, Gautam Tiwari, Anirudh Raju, Jasha Droppo, Ariya Rastrow, and Andreas Stolcke. 2021. Do as i mean, not as i say: Sequence loss training for spoken language understanding. In *Proc. of ICASSP*.
- Chenze Shao, Jinchao Zhang, Jie Zhou, and Yang Feng. 2023. Rephrasing the reference for non-autoregressive machine translation. In *Proc. of AAAI*.
- Rohan Shet, Elena Davcheva, and Christian Uhle. 2019. Segmenting multi-intent queries for spoken language understanding. *Studentexte zur Sprachkommunikation: Elektronische Sprachsignalverarbeitung 2019*.
- Mengxiao Song, Bowen Yu, Li Quangang, Wang Yubin, Tingwen Liu, and Hongbo Xu. 2022. Enhancing joint multiple intent detection and slot filling with global intent-slot co-occurrence. In *Proc. of EMNLP*.
- Gokhan Tur and Renato De Mori. 2011. *Spoken language understanding: Systems for extracting semantic information from speech*. John Wiley & Sons.
- Petar Velickovic, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Liò, and Yoshua Bengio. 2018. Graph attention networks. In *Proc. of ICLR*.
- Yu Wang, Abhishek Patel, Yilin Shen, and Hongxia Jin. 2018a. A deep reinforcement learning based multimodal coaching model (DCM) for slot filling in spoken language understanding (slu). In *Proc. of INTERSPEECH*.

- Yu Wang, Yilin Shen, and Hongxia Jin. 2018b. A bi-model based RNN semantic frame parsing model for intent detection and slot filling. In *Proc. of NAACL*.
- Yucheng Wang, Zhongyu Wei, Yaqian Zhou, and Xuanjing Huang. 2018c. Automatic essay scoring incorporating rating schema via reinforcement learning. In *Proc. of EMNLP*.
- Ronald J Williams. 1992. Simple statistical gradient-following algorithms for connectionist reinforcement learning. *Machine learning*.
- Di Wu, Liang Ding, Fan Lu, and Jian Xie. 2020. SlotRe-fine: A fast non-autoregressive model for joint intent detection and slot filling. In *Proc. of EMNLP*.
- Lijun Wu, Fei Tian, Tao Qin, Jianhuang Lai, and Tie-Yan Liu. 2018. A study of reinforcement learning for neural machine translation. In *Proc. of EMNLP*.
- Congying Xia, Chenwei Zhang, Xiaohui Yan, Yi Chang, and Philip Yu. 2018. Zero-shot user intent detection via capsule neural networks. In *Proc. of EMNLP*.
- Bowen Xing and Ivor Tsang. 2022a. Co-guiding net: Achieving mutual guidances between multiple intent detection and slot filling via heterogeneous semantics-label graphs. In *Proc. of EMNLP*.
- Bowen Xing and Ivor Tsang. 2022b. Group is better than individual: Exploiting label topologies and label relations for joint multiple intent detection and slot filling. In *Proc. of EMNLP*.
- Bowen Xing and Ivor W Tsang. 2023. Relational temporal graph reasoning for dual-task dialogue language understanding. *IEEE Transactions on Pattern Analysis and Machine Intelligence*.
- Caiming Xiong, Victor Zhong, and Richard Socher. 2018. DCN+: mixed objective and deep residual coattention for question answering. In *Proc. of ICLR*.
- Jingjing Xu, Xu Sun, Qi Zeng, Xiaodong Zhang, Xuancheng Ren, Houfeng Wang, and Wenjie Li. 2018. Unpaired sentiment-to-sentiment translation: A cycled reinforcement learning approach. In *Proc. of ACL*.
- Puyang Xu and Ruhi Sarikaya. 2013. Convolutional neural network based triangular crf for joint intent detection and slot filling. In *2013 IEEE workshop on automatic speech recognition and understanding*.
- Steve Young, Milica Gašić, Blaise Thomson, and Jason D Williams. 2013. Pomdp-based statistical spoken dialog systems: A review. *Proceedings of the IEEE*.
- Jiwen Yu, Xuanyu Zhang, Youmin Xu, and Jian Zhang. 2023. Cross: Diffusion model makes controllable, robust and secure image steganography. *ArXiv preprint*.
- Dong Zhang, Rong Ye, Tom Ko, Mingxuan Wang, and Yaqian Zhou. 2023a. DUB: Discrete unit back-translation for speech translation. In *Proc. of ACL Findings*.
- Junzi Zhang, Jongho Kim, Brendan O’Donoghue, and Stephen P. Boyd. 2021. Sample efficient reinforcement learning with REINFORCE. In *Proc. of AAAI*.
- Kexun Zhang, Rui Wang, Xu Tan, Junliang Guo, Yi Ren, Tao Qin, and Tie-Yan Liu. 2022a. A study of syntactic multi-modality in non-autoregressive machine translation. In *Proc. of NAACL*.
- Xin Zhang, Dong Zhang, Shimin Li, Yaqian Zhou, and Xipeng Qiu. 2023b. Spechtokenizer: Unified speech tokenizer for speech large language models. *ArXiv preprint*.
- Xuanyu Zhang, Yongbing Zhang, Ruiqin Xiong, Qilin Sun, and Jian Zhang. 2022b. Herosnet: Hyperspectral explicable reconstruction and optimal sampling deep network for snapshot compressive imaging. In *Proc. of CVPR*.
- Zhihong Zhu, Xuxin Cheng, Zhiqi Huang, Dongsheng Chen, and Yuexian Zou. 2023a. Enhancing code-switching for cross-lingual slu: A unified view of semantic and grammatical coherence. In *Proc. of EMNLP*.
- Zhihong Zhu, Xuxin Cheng, Zhiqi Huang, Dongsheng Chen, and Yuexian Zou. 2023b. Towards unified spoken language understanding decoding via label-aware compact linguistics representations. In *Proc. of ACL Findings*.
- Zhihong Zhu, Weiyuan Xu, Xuxin Cheng, Tengtao Song, and Yuexian Zou. 2023c. A dynamic graph interactive framework with label-semantic injection for spoken language understanding. In *Proc. of ICASSP*.