MULTI-GRAINED LABEL REFINEMENT NETWORK WITH DEPENDENCY STRUCTURES FOR JOINT INTENT DETECTION AND SLOT FILLING

Baohang Zhou, Ying Zhang*, Xuhui Sui, Kehui Song, Xiaojie Yuan

College of Computer Science, TKLNDST, Nankai University, China

ABSTRACT

Slot filling and intent detection are two fundamental tasks in the field of natural language understanding. Due to the strong correlation between these two tasks, previous studies make efforts on modeling them with multi-task learning or designing feature interaction modules to improve the performance of each task. However, none of the existing approaches consider the relevance between the structural information of sentences and the label semantics of two tasks. The intent and semantic components of a utterance are dependent on the syntactic elements of a sentence. In this paper, we investigate a multi-grained label refinement network, which utilizes dependency structures and label semantic embeddings. Considering to enhance syntactic representations, we introduce the dependency structures of sentences into our model by graph attention layer. To capture the semantic dependency between the syntactic information and task labels, we combine the task specific features with corresponding label embeddings by attention mechanism. The experimental results demonstrate that our model achieves the competitive performance on two public datasets.

Index Terms— Intent Detection, Slot Filling, Label Refinement, Dependency Parsing

1. INTRODUCTION

Slot filling and intent detection are two critical tasks for natural language understanding (NLU). The two tasks are defined to identify intents and extract semantic components from utterances in dialog systems [1]. Intent detection is formulated as a sentence-level classification problem, and slot filling can be regarded as a sequence labeling problem. Traditional methods tend to solve the two tasks independently. For intent detection, researchers applied traditional machine learning methods, such as logistic regression, random forest, and deep belief networks [2]. The sequence-based models, such as long short-term memory (LSTM) [3] and conditional random fields (CRF) [4], have achieved significant performances on slot filling.

Considering the relevance between intent detection and slot filling, some works proposed joint models to tackle the two tasks with feature interaction between them. Previous joint learning methods utilized the supervised signal from intent detection to improve the performance of slot filling by attention [5] or gated [6] mechanisms. Recently, Qin et al. [7] proposed a co-interactive module to model the cross-impact of two tasks and achieved the state-of-the-art performance. The joint learning methods always demonstrate their effectiveness over the independent models [8, 9, 10]. However, the existing methods do not take the advantage of the correlation between the syntactic information and target label semantics. The syntactic information implies the dependency structures of sentences. And the objects of prepositional phrases are often slot values to be extracted in a sentence while the intent of speakers can be reflected by the verbs. Therefore, it is a meaningful way to exploit the dependency structures of syntactic for enhancing the sentence representations cooperated with label semantics.

To address the limitations of existing approaches, we propose a multi-grained label refinement network with dependency structures for jointly modeling slot filling and intent detection. When utilizing the syntactic knowledge, Wang et al. [11] proposed an task to predict the dependency matrix. Considering the variant importance of syntactic characteristics in dependency structures, we encode the syntactic information by graph attention network [12]. Furthermore, we acquire the semantic embeddings of task labels by their descriptions [13]. Through the attention mechanism [14], we fuse the syntactic-enhanced sentence features with prior label semantics of slot filling and intent detection. The above operations can bridge the gap between the syntactic information and label semantics, improving the performance of the two tasks.

We compare our model with several state-of-the-art baselines on two public datasets: ATIS [15] and SNIPS [16]. The experimental results demonstrate that our model can achieve significant improvements on different metrics.

2. MODEL

The overall model is shown in Fig. 1. Before presenting the details of our model, we introduce the notations about the slot filling and intent detection. For slot filling, we denote \( \{(X_i, y_i^S)\}_{i=1}^{N_s} \) as a training set with \( N_s \) samples, where \( X_i \) is the utterance text and \( y_i^S \) is slot filling label. Given a sen-
tence with \( N_w \) words, the utterance text can be formulated as \( X = \{x_i\}_{i=1}^{N_w} \) and the slot filling label is \( y^S = \{y_i\}_{i=1}^{N_w} \). The location of slot entity is more related to the syntactic of sentence and the type of slot entity is more related to the semantic of sentence. Therefore, in our model, we split the slot filling labels \( y^S \) into two parts: BIO labels \( y^{ss} = \{y^{ss}_i\}_{i=1}^{N_w} \) and slot entity types \( \{l_k, r_k, y^{st}_k\}_{1 \leq l_k \leq r_k \leq N_w, k \in [1, N_s]} \), where \( l_k \) and \( r_k \) are the start and end indexes of \( k \)-th slot entity and \( y^{st}_k \) is the type of it in sentence. For example, the original label sequence “O B-round_trip I-round_trip” is reformulated as “O B I” and “(2,3,”round_trip”). For slot filling, we should predict BIO labels to locate slot entity first and then acquire the types of predicted slot entities. Besides, we denote \( \{X_i, y^I_i\}_{i=1}^{N_w} \) as a intent detection training set.

2.1. Pre-trained Language Model

To map the discrete words of sentences into the dense distributed representations, we utilize the pre-trained language model BERT [17] as feature extractor. The BERT architecture can capture the contextual features of sentences effectively. Given the input sentence \( X \), we should insert special tokens \([CLS]\) and \([SEP]\) into the start and end of the sentence. And the feature extraction process can be simplified as \( \text{BERT}(X) = \{h_i\}_{i=1}^{N_w+1}, \) where \( h_0 \) is the dense vector of token \([CLS]\), \( \{h_i\}_{i=1}^{N_w} \) is the language representations of input sentence and \( h_i \in \mathbb{R}^d \). \( d \) is the dimension number of vector extracted from BERT.

2.2. Dependency Structures Encoder

The most important contribution of our model is that we exploit the syntactic structural information to enhance the representations of sentences. Given the input sentence, we utilize the Stanford CoreNLP toolkit to acquire the syntactic structures. According to the direct information of dependency parsing tree, we construct a adjacency matrix \( A \in \mathbb{R}^{(N_w+2) \times (N_w+2)} \) as shown in Fig. 1. To capture the graph structural information, we make efforts on the graph neural networks to encode the syntactic knowledge into our model. Furthermore, we consider the importance of various syntactic elements and utilize graph attention network (GAT) [12] to enhance the representations of sentences. After acquiring the features \( H = \{h_i\}_{i=0}^{N_w+1} \), we feed them into a typical GAT and the syntactic-enhanced feature is \( G = \{g_i\}_{i=0}^{N_w+1} \). The calculation process of GAT can be simplified as \( g_i = \|K\| \sigma(\sum_{j \in n(i) \alpha_{ij} W_k^{ij} h_j}), \) \( \alpha_{ij} = \frac{\exp(\text{LeakyRelu}(a^e_{ij} W_k^{ij} h_i, \|W_k^{ij} h_i\|)))}{\sum_{j \in n(i) \exp(\text{LeakyRelu}(a^e_{ij} W_k^{ij} h_i, \|W_k^{ij} h_i\|)))} \), where \( \| \) is the concatenation of vectors, \( W_k^{ij} \) and \( \alpha_{ij} \) are trainable weights of \( k \)-th multi-head attention, \( n[i] \) is the neighbors of input feature \( h_i \) according to the adjacency matrix \( A \).

2.3. Intent Detection Procedure

The token \([CLS]\) is the aggregation placeholder and its corresponding feature vector \( g_0 \) can be utilized to predict the intent type directly [18]. Considering label semantics are helpful to refine the intent labels [19], we construct the intent label embedding \( E^I = \{e^I_i\}_{i=1}^{I_{label}} \), where \( I_{label} \) is the number of intent label. The intent label embedding is composed by the description semantic embedding \( E^S \in \mathbb{R}^{I_{label} \times d} \) and global semantic embedding \( W^G \in \mathbb{R}^{I_{label} \times d} \), where the former is fixed and the latter is trainable. We feed each label description into BERT and concatenate the compressed feature vectors of label descriptions as \( E^S \). Besides, to capture the global semantic of intents, we initialize the trainable weights as global semantic embedding \( W^G \). To focus on the most correlated label semantics, we utilize the attention mechanism [14] to fuse the syntactic-enhanced features with intent label embedding. The attention weighted features can be calculated as: \( h^I = \text{Attention}(g_0, E^I; W_a, b_a) = \sum_{i=1}^{I_{label}} \beta_i e^I_i \), where the attention score is defined as \( \beta_i = \frac{\exp(W_a e^I_i \|g_0\|+b_a)}{\sum_{j=1}^{I_{label}} \exp(W_a e^I_j \|g_0\|+b_a)} \). \( W_a \) and \( b_a \) are trainable weights in the intent label atten-
2.4. Slot Filling Procedure

In our model, there are two steps to perform slot filling. The first step is to predict BIO labels for extracting slot entities. In the second step, we predict the types of the above extracted slot entities. The intent label-enhanced feature is focused on the tokens correlated to sentence intents and helpful to extract slot entities. Therefore, we propose the intent semantic gated mechanism to guide the model to locate slot entities. The formulation of the gated mechanism is \( \text{Gate}(\mathbf{H}', \mathbf{G}) = \sigma (\mathbf{W}_s [\mathbf{H}' || \mathbf{G}] + \mathbf{b}_g) \) where \( \sigma \) is the sigmoid function and \( \mathbf{H}' = [\mathbf{h}_1; \ldots; \mathbf{h}_l] \in \mathbb{R}^{l \times (N_w + 2)} \). Considering the semantic difference of the syntactic-enhanced features and raw language ones, we combine the two parts and the fusion sentence feature is \( \mathbf{H}^S = \text{Gate}(\mathbf{H}', \mathbf{G}) \odot \mathbf{G}[\mathbf{H}] \) where \( \odot \) is the element-wise production. We utilize the fusion feature to predict the BIO label probabilities \( \hat{y}_i^s = \text{softmax} (\mathbf{W}_0 \mathbf{h}^S_0 + \mathbf{b}_0) \). The loss function of this step is defined as \( \mathcal{L}_{\text{slot1}} = -\sum_{i=1}^{N_s} \sum_{j=1}^{N_e} \hat{y}_{ij}^s \log \hat{y}_{ij}^s \) in which \( \hat{y}_{ij}^s \) is the BIO label probabilities of the \( j \)th token in the \( i \)th sample. To predict the type of each slot entity, we utilize the raw language features of spans as representations: \( r_k = \sum_{i \in S_k} \mathbf{h}_i \). To utilize the label semantics for refining the slot labels, we also construct the slot label embedding \( \mathbf{E}_i^S = \{e_{i,j}^S \}_{j=1}^{|S_{lab}|} \) as the way for intent label embedding. The label semantic features are fused with language features as \( \mathbf{h}_i^S = \text{Attention}(r, \mathbf{E}_i^S; \mathbf{W}_v, \mathbf{b}_v) \). We predict the type of slot entity as \( \hat{y}_{ik}^s = \text{softmax} (\mathbf{W}_2 \mathbf{h}_i^S + \mathbf{b}_2) \). The loss function of the second step is \( \mathcal{L}_{\text{slot2}} = -\sum_{k=1}^{N_k} \sum_{i=1}^{N_e} \hat{y}_{ik}^s \log \hat{y}_{ik}^s \) where \( \hat{y}_{ik}^s \) is the type probabilities of the \( k \)th slot entity in the \( i \)th sample.

2.5. Training Procedure

To tackle the slot filling and intent detection tasks at once, we introduce the hyper-parameter to sum the loss functions \( \mathcal{L}_{\text{intent}}, \mathcal{L}_{\text{slot1}} \) and \( \mathcal{L}_{\text{slot2}} \). The overall loss function for the joint learning model is defined as: \( \mathcal{L} = (1 - \gamma) \cdot (\mathcal{L}_{\text{slot1}} + \mathcal{L}_{\text{slot2}}) + \gamma \cdot \mathcal{L}_{\text{intent}} \) where \( \gamma \) is the hyper-parameter for balancing different task losses. For training the model, we feed the training samples into it and calculate the overall loss by the above equation. And then we utilize the stochastic gradient descent method to update the parameters of the model.

3. EXPERIMENTS

We compare our model with baseline methods on two public datasets. The airline travel information systems (ATIS) dataset contains recordings of people having flight services [15]. The SNIPS dataset covers utterances of different domains, such as: weather, restaurants and entertainment [16]. Both two original datasets are not split into training, validation and test sets. We follow the same format and partition of datasets as in Qin et al. [20].

The hyper-parameter settings of our model on two dataset are shown in Table 1. And we use Adam [21] algorithm to optimize the trainable parameters in our model. To compare with different models, we evaluate performance of slot filling using entity-level F1 score, intent detection using accuracy and sentence-level semantic parsing using overall accuracy. We save the best model which achieves the highest score on the validation set and report the results of it on the test set.

In this paper, we utilize the BERT-large version of pre-trained model BERT as language model. To demonstrate the effectiveness of the proposed method fairly, we compare our model with BERT-based models, such as Stack-Propagation [20], BERT-joint [18], SlotRefine [22] and SyntacticTF [11]. Besides, we also select LSTM-based models as baselines to show the superiority of pre-trained language model and the effectiveness of our model.

### Table 1. The hyper-parameter settings for our model on the ATIS and SNIPS datasets.

| Hyper-parameter | ATIS | SNIPS |
|-----------------|------|-------|
| \( \gamma \)    | 0.6  | 0.5   |
| batch size      | 16   | 14    |
| learning rate   | 1e-5 | 1e-5  |
| # graph attention head | 4  | 2    |
| graph attention dropout rate | 0.4 | 0.5 |
| # graph attention output features | 256 | 512   |

3.1. Experimental Results

The detailed experiment results on ATIS and SNIPS are shown in Table 2. Conventional joint learning models, such as Slot-Gated [6] and CapsuleNLU [9], utilized the intent information to improve the performance of slot filling. Wu et al. proposed SlotRefine with two-stage training process for refining intent and slot labels [22]. SyntacticTF [11] introduced dependency parsing prediction task into slot filling and intent detection joint learning model, and achieved the state-of-the-art results. Compared with existing methods, we bridge the gap between the syntactic information and task label semantics. While utilizing syntactic knowledge to enhance the representations of sentences, we also exploit the slot-level and intent-level label semantic features with attention mechanism to improve the performance of two tasks.

Our model does not only achieve competitive scores on unilateral evaluation metrics but also gain significant im-
Table 2. Performances of different models on two datasets. The results of ablation study for our model are also presented.

| Model                           | ATIS               | SNIPS               |
|---------------------------------|--------------------|--------------------|
|                                 | Slot (F1) Intent (Acc) Semantic (Acc) | Slot (F1) Intent (Acc) Semantic (Acc) |
| Attention-based RNN [15]        | 94.20 91.10 78.90  | 87.80 96.70 74.10  |
| Joint Seq [8]                   | 94.30 92.60 80.70  | 87.30 96.90 73.20  |
| Slot-Gated [2]                  | 95.20 94.10 82.60  | 94.60 97.40 87.20  |
| CapsuleNLU [9]                  | 95.60 96.60 86.20  | 91.80 97.30 80.90  |
| BiLSTM-CRF [23]                 | 95.62 97.42 87.35  | 93.90 99.29 85.43  |
| ELMo [24]                       | 96.10 97.50 88.20  | 97.00 98.60 92.80  |
| Stack-Propagation [20]          | 96.10 97.50 88.60  | 97.00 99.00 92.90  |
| GraphLSTM [25]                  | 95.91 97.20       | 95.30 98.29       |
| SlotRefine [22]                 | 96.16 97.74 88.64 | 97.05 99.04 92.96 |
| SyntacticTF [11]                | 96.01 97.31       | 96.89 99.14       |
| Ours                            | 96.28 98.78 89.79 | 97.17 98.51 93.26 |
| w/o slot label attention module | 95.89 98.50 88.54 | 96.50 98.32 92.10 |
| w/o intent label attention module | 96.10 98.10 88.42 | 96.78 98.10 92.25 |
| w/o dependency structures encoder | 96.03 98.17 88.40 | 96.36 98.14 91.24 |

3.2. Ablation Study

Impact of Slot Label Attention Module We remove the slot label attention module and directly use the span features \( r \) to predict the slot entity types. The results of experiment “w/o slot label attention module” are presented in Table 2. We can observe that the slot filling performance decreased the most, which demonstrates the slot label semantics are critical to the slot filling procedure. Besides, the intent detection performance also drops a little, and the implicit correlation between intent detection and slot filling influences the performances of each other.

Impact of Intent Label Attention Module After removing the intent label attention module, we feed the language representation \( h_0 \) of token [CLS] into the intent semantic gated mechanism and use it to predict the intent labels. The results of experiment “w/o intent label attention module” are shown in Table 2. We can observe that the performance of intent detection decreased the most while the slot filling performance also declined to a certain extent. This phenomenon verifies that intent label semantics play an important role in the intent detection and are beneficial to improving the slot filling performance.

Impact of Dependency Structures Encoder To prove the effectiveness of syntactic knowledge, we conduct the experiment “w/o dependency structures encoder” as shown in Table 2 and utilize language representations \( H \) to perform slot filling and intent detection. We can observe that the slot filling and intent detection performances both declined a lot. This proves that the prior syntactic knowledge is critical to the two tasks. The dependency structural information is encoded by GAT and enhances the representations of sentences to improve the performance of slot filling and intent detection.

4. CONCLUSION

In this paper, we propose a multi-grained label refinement network with dependency structures. Considering the implicit correlation between syntactic knowledge and task label semantics, we encode the dependency structural information by graph attention network, and utilize slot and intent label attention modules to fuse the syntactic-enhanced features with label semantic ones. Experimental results on two benchmarks demonstrate the superiority of our model. In the future, we will tackle cross-domain slot filling and intent detection with prior knowledge driven models.

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6. REFERENCES

[1] Henry Weld, Xiaoqi Huang, Siqi Long, Josiah Poon, and Soyeon Caren Han, “A survey of joint intent detection and slot-filling models in natural language understanding,” CoRR, 2021.

[2] Gokhan Tur, Spoken Language Understanding: Systems for Extracting Semantic Information from Speech, 2011.

[3] Sepp Hochreiter and Jürgen Schmidhuber, “Long short-term memory,” Neural Comput., 1997.

[4] John D. Lafferty, Andrew McCallum, and Fernando C. N. Pereira, “Conditional random fields: Probabilistic models for segmenting and labeling sequence data,” in Proc. of ICML, 2001.

[5] Bing Liu and Ian R. Lane, “Attention-based recurrent neural network models for joint intent detection and slot filling,” in ISCA, 2016.

[6] Chih-Wen Goo, Guang Gao, Yun-Kai Hsu, Chih-Li Huo, Tsung-Chieh Chen, Keng-Wei Hsu, and Yun-Nung Chen, “Slot-gated modeling for joint slot filling and intent prediction,” in Proc. of NAACL, 2018.

[7] Libo Qin, Tailu Liu, Wanxiang Che, Bingbing Kang, Sendong Zhao, and Ting Liu, “A co-interactive transformer for joint slot filling and intent detection,” in Proc. of ICASSP, 2021.

[8] Dilek Hakkani-Tür, Gökhan Tür, Aslı Celikyilmaz, Yun-Nung Chen, Jianfeng Gao, Li Deng, and Ye-Yi Wang, “Multi-domain joint semantic frame parsing using bi-directional RNN-LSTM,” in ISCA, 2016.

[9] Chenwei Zhang, Yaliang Li, Nan Du, Wei Fan, and Philip S. Yu, “Joint slot filling and intent detection via capsule neural networks,” in Proc. of ACL, 2019.

[10] Yanfei Hui, Jianzong Wang, Ning Cheng, Fengying Yu, Tianbo Wu, and Jing Xiao, “Joint intent detection and slot filling based on continual learning model,” in Proc. of IJCAI, 2021.

[11] Jixuan Wang, Kai Wei, Martin Radfar, Weiwei Zhang, and Clement Chung, “Encoding syntactic knowledge in transformer encoder for intent detection and slot filling,” in Proc. of AAAI, 2021.

[12] Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Liò, and Yoshua Bengio, “Graph Attention Networks,” ICLR, 2018.

[13] Su Zhu, Zijian Zhao, Rao Ma, and Kai Yu, “Prior knowledge driven label embedding for slot filling in natural language understanding,” IEEE TASLP, 2020.

[14] Peng Zhou, Wei Shi, Jun Tian, Zhenyu Qi, Bingchen Li, Hongwei Hao, and Bo Xu, “Attention-based bidirectional long short-term memory networks for relation classification,” in Proc. of ACL, 2016.

[15] Charles T. Hemphill, John J. Godfrey, and George R. Doddington, “The ATIS spoken language systems pilot corpus,” in Speech and Natural Language: Proceedings of a Workshop Held at Hidden Valley, 1990.

[16] Alice Coucke, Alaa Saade, Adrien Ball, Théodore Bluche, Alexandre Caulier, David Leroy, Clément Doumouro, Thibault Gisselbrecht, Francesco Caltagirone, Thibaut Lavril, Maël Primet, and Joseph Dureau, “Snips voice platform: an embedded spoken language understanding system for private-by-design voice interfaces,” CoRR, 2018.

[17] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova, “BERT: pre-training of deep bidirectional transformers for language understanding,” in Proc. of NAACL, 2019.

[18] Qian Chen, Zhu Zhuo, and Wen Wang, “BERT for joint intent classification and slot filling,” CoRR, 2019.

[19] Leyang Cui and Yue Zhang, “Hierarchically-refined label attention network for sequence labeling,” in Proc. of EMNLP-IJCNLP, 2019.

[20] Libo Qin, Wanxiang Che, Yangming Li, Haoyang Wen, and Ting Liu, “A stack-propagation framework with token-level intent detection for spoken language understanding,” in Proc. of EMNLP-IJCNLP, 2019.

[21] Diederik P. Kingma and Jimmy Ba, “Adam: A method for stochastic optimization,” in ICLR, 2015.

[22] Di Wu, Liang Ding, Fan Lu, and Jian Xie, “Slotrefine: A fast non-autoregressive model for joint intent detection and slot filling,” in Proc. of EMNLP, 2020.

[23] Fatima Zohra Daha and Sanjika Hewavitharana, “Deep neural architecture with character embedding for semantic frame detection,” in 13th IEEE International Conference on Semantic Computing, 2019.

[24] Aditya Siddhant, Anuj Kumar Goyal, and Angeliki Metallinou, “Unsupervised transfer learning for spoken language understanding in intelligent agents,” in Proc. of AAAI, 2019.

[25] Linhao Zhang, Dehong Ma, Xiaodong Zhang, Xiaohui Yan, and Houfeng Wang, “Graph LSTM with context-gated mechanism for spoken language understanding,” in Proc. of AAAI, 2020.