HAN: Higher-order Attention Network for Spoken Language Understanding

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Abstract
Spoken Language Understanding (SLU), including intent detection and slot filling, is a core component in human-computer interaction. The natural attributes of the relationship among the two subtasks make higher requirements on fine-grained feature interaction, i.e., the token-level intent features and slot features. Previous works mainly focus on jointly modeling the relationship between the two subtasks with attention-based models, while ignoring the exploration of attention order. In this paper, we propose to replace the conventional attention with our proposed Bilinear attention block and show that the introduced Higher-order Attention Network (HAN) brings improvement for the SLU task. Importantly, we conduct wide analysis to explore the effectiveness brought from the higher-order attention.

1 Introduction
Intent detection (ID) and Slot filling (SF) play important roles in SLU system. For instance, given an utterance "I want to listen to Hey Jude", ID can be seen as a classification task to identify the user’s intent is to listen to a song and SF can be treated as a sequence labeling task to produce a slot label sequence in BIO format (Ramshaw and Marcus, 1999; Zhang and Wang, 2016) which demonstrate that Hey Jude is the song’s title. Table 1 shows the expected output of SLU system for this instance.

Taking into account the relationship between these two tasks, joint modeling of them has gradually become the dominant method recently (Goo et al., 2018; Liu et al., 2019b; Niu et al., 2019; Qin et al., 2019, 2020; Huang et al., 2020; Zhou et al., 2020; Huang et al., 2021c). The state-of-the-art methods (Li et al., 2018; Qin et al., 2019, 2020) adopt the attention mechanism (Vaswani et al., 2017) to trigger the mutual interaction between intent features and slot features. Concretely, the attention mechanism learns a set of weights which reflect the importance of different words of an utterance via linearly fusing the given query and key via element-wise sum, and the weights are then applied to the value to derive a weighted sum which represents the enhanced intent or slot representation in a co-interactive way.

In this paper, we argue that the inherent design of conventional attention mechanism can only model the 1st order feature interaction between query and key, which, however, is inefficient to model the relationship between ID and SF. Therefore, to obtain more representative intent and slot features, we propose to exploit higher-order interactions from 2nd order feature interaction via bilinear pooling, which is an operation to calculate outer product between two feature vectors. Such technique can enable the 2nd order feature interaction by taking all pair-wise interactions between query and key into account and thus provide more discriminative representations. Lin et al. (2015) first applied bilinear pooling to fuse visual features for fine-grained visual recognition. In order to mitigate the high computational complexity of bilinear pooling, Kim et al. (2016) proposed low-rank bilinear pooling with linear mapping and Hadamard product. Inspired by the successful application of bilinear pooling in the field of Computer Vision research, we proposed our BiLinear attention block as shown in Figure 1, which can build the 2nd order interactions between intent and slot features and get more discriminative intent and slot representations. Intuitively, a stack of the blocks is readily grouped to go beyond bilinear models and extract higher-order interactions.
To this end, we also provide the view of how to integrate such blocks into HAN for building higher-order feature interactions. The experiments show that our model achieves new state-of-the-art results on two benchmark datasets SNIPS (Coucke et al., 2018) and ATIS (Hemphill et al., 1990).

2 Approach

We briefly formulate our HAN (Figure 2) which consists of four parts and introduce our BiLinear attention block in detail.

2.1 BiLinear attention block

In this section, we will describe the proposed BiLinear attention block as shown in Figure 1 in detail.

Suppose we have a query \( q \in \mathbb{R}^d \), a set of keys \( K = \{k_i\}_{i=1}^n \), and a set of values \( V = \{v_i\}_{i=1}^n \), where \( k_i, v_i \in \mathbb{R}^d \) denote the \( i \)-th key/value pair. Our block first performs low-rank bilinear pooling (Kim et al., 2016) to achieve a joint bilinear query-key representation \( B_i^k \in \mathbb{R}^d \) to model the 2\( ^{nd} \) order feature interactions between query and key: \( B_i^k = \text{ReLU}(W_k k_i) \odot \text{ReLU}(W_v v_i q) \), where \( W_k, W_v \in \mathbb{R}^{d \times d} \) are weight matrices.

Next, depending on all bilinear query-key representations \( \{B_i^k\}_{i=1}^n \), two kinds of bilinear attention distributions are obtained to aggregate both contextual and channel-wise information within all values. Specifically, the contextual bilinear attention distribution is introduced by projecting each bilinear query-key representation into the corresponding attention weight via two embedding layers, followed with a softmax layer for normalization:

\[
B_i^k = \text{ReLU}(W_k k_i) : b_i^k = \text{ReLU}(W_v v_i q) ; \\
\beta_i^k = \text{softmax}(b_i^k),
\]

where \( W_k \in \mathbb{R}^{d \times d} \) and \( W_v \in \mathbb{R}^{1 \times d} \) are weight matrices, \( B_i^k \) is the transformed bilinear query-key representation, and \( b_i^k \) is the \( i \)-th element in \( b_i^k \).

Here each element \( \beta_i^k \) in \( \beta^k \) denotes the normalized contextual attention weight for each key/value pair. Meanwhile, we perform a squeeze-excitation operation over all transformed bilinear query-key representations \( \{B_i^k\}_{i=1}^n \) for channel-wise attention measurement. Concretely, the operation of squeeze aggregates all transformed bilinear query-key representations via average pooling, leading to a global channel descriptor \( \overline{B} = \frac{1}{n} \sum_{i=1}^n B_i^k \). After that, the followed excitation operation produces channel-wise attention distribution \( \beta^c \) by leveraging the self-gating mechanism with a sigmoid function over the \( \overline{B} \):

\[
b^c = W_e, \overline{B}, \beta^c = \sigma(b^c),
\]

where \( W_e \in \mathbb{R}^{d \times d} \) is weight matrix.

Finally, our BiLinear attention block generates the attended value feature \( v_i \) by accumulating the enhanced bilinear values with contextual and channel-wise bilinear attention:

\[
\hat{v}_i = \beta^c \odot \sum_{i=1}^n \beta_i^k B_i^c, \ 
B_i^c = \text{ReLU}(W_v v_i) \odot \text{ReLU}(W_v v_i q),
\]

where \( B_i^c \) denotes the enhanced value of bilinear pooling on query \( q \) and each value \( v_i \), \( W_v \in \mathbb{R}^{d \times d} \) and \( W_v \in \mathbb{R}^{d \times d} \) are weight matrices. As such, BiLinear attention block produces more representative attended feature since higher-order feature interactions are exploited via bilinear pooling. We iterate the above process \( n \) times with \( Q = \{q_i\}_{i=1}^n \), and get a set of values \( \hat{V} = \{\hat{v}_i\}_{i=1}^n \) :

\[
\hat{V} = \mathcal{F}_{\text{BiLinear}}(K, V, Q),
\]

where \( \hat{V} \in \mathbb{R}^{n \times d} \) is the enhanced features with higher-order attention feature interactions. By equipping the block with Exponential Linear Unit (ELU) (Barron, 2017), it can model infinity order feature interactions, which can be proved via Taylor expansion of each element in bilinear vector after

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Figure 1: The proposed BiLinear attention block, which is based on the low-rank bilinear pooling (Kim et al., 2016).

Figure 2: Architecture of the proposed HAN.
exponential transformation. Specifically, for two vectors $X$ and $Y$, their exponential bilinear pooling can be estimated using the Taylor expansion:

$$
\exp(W_X X) \odot \exp(W_Y Y)
= \exp(W_X^1 X) \odot \exp(W_Y^1 Y) \ldots \exp(W_X^D X) \odot \exp(W_Y^D Y)
= \sum_{p=0}^{\infty} \frac{1}{p!} (W_X^p X + W_Y^p Y)^p \ldots \sum_{p=0}^{D} \frac{1}{p!} (W_X^p X + W_Y^p Y)^p,
$$

where $W_X$ and $W_Y$ are embedding matrices, $D$ denotes the dimension of bilinear vector, $W_X^i/W_Y^i$ is the $i$-th row in $W_X/W_Y$.

### 2.2 Overview of the HAN

**Self-attentive Embedder**  Inspired by Qin et al. (2019), we employ the Self-attentive Embedder to obtain the utterance embeddings. It first uses a shared BiLSTM to embed the input sequence, acquiring $H = (h_1, h_2, ..., h_n)$. Then, it performs the label attention (Cui and Zhang, 2019) over intent and slot label to get the explicit intent and slot representation $H_I \in \mathbb{R}^{n \times d}$, $H_S \in \mathbb{R}^{n \times d}$ ($d = 128$), which capture the intent and slot semantic information, respectively.

**Higher-order Attention Encoder**  $H_I$ and $H_S$ are further fed into the our Higher-order Attention Encoder to strengthen both the intent and slot features via capturing higher-order feature interactions between them. Formally, the encoder is composed of a stack of $N = 2$ identical sublayers. Each sublayer is our Bilinear attention block, followed by layer normalization. Same with Vaswani et al. (2017), we first map the matrix $H_I$ and $H_S$ to queries($Q^{(1)}_I, Q^{(1)}_S$), keys($K^{(1)}_I, K^{(1)}_S$) and values($V^{(1)}_I, V^{(1)}_S$) matrices by using different linear projections. Then we take $Q^{(1)}_I, K^{(1)}_S$ and $V^{(1)}_S$ as queries, keys and values, respectively, acquiring the enhanced values:

$$
V^{(2)}_I = F_{\text{BiLinear}} (K^{(1)}_I, V^{(1)}_S, Q^{(1)}_I),
$$

$$
H^{(2)}_I = \text{LN}(H_I + V^{(1)}_I),
$$

where LN represents the layer normalization (Ba et al., 2016). Similarly, we take $Q^{(1)}_S$ as queries, $K^{(1)}_I$ as keys and $V^{(1)}_I$ as values to obtain $H^{(1)}_S$.

After repeating $N$ times, we can obtain the enhanced intent features $H^{(N)}_I \in \mathbb{R}^{n \times d}$ and slot features $H^{(N)}_S \in \mathbb{R}^{n \times d}$, which are endowed with the higher-order feature interactions in between.

**Dynamic Feature Fusion Layer**  We first compute two weight matrices $\alpha_I$ and $\alpha_S$ which reflect the relevance between the output and the input query of the last sublayer in the Higher-order Attention Encoder, and thus obtain the fused features $H_{IS}$, which can be defined as follows:

$$
\alpha_I = \sigma(W_I [Q^{(N)}_I, H^{(N)}_I] + b_I),
$$

$$
\alpha_S = \sigma(W_S [Q^{(N)}_S, H^{(N)}_S] + b_S),
$$

$$
H_{IS} = \alpha_I \odot H^{(N)}_I + \alpha_S \odot H^{(N)}_S,
$$

where $[\cdot, \cdot]$ indicates concatenation, $\sigma$ is the sigmoid activation; $\odot$ denotes element-wise multiplication; $W_I$ and $W_S$ are both $2d \times d$ embedding matrices, $b_I$ and $b_S$ are biases. Then, we adopt the feed-forward network (FFN) (Zhang and Wang, 2016), to acquire the updated intent features $\tilde{H}^{(N)}_I \in \mathbb{R}^{n \times d}$ and slot features $\tilde{H}^{(N)}_S \in \mathbb{R}^{n \times d}$, i.e.,

$$
\tilde{H}^{(N)}_I = \text{LN}(\text{FFN}(H_{IS}) + H^{(N)}_I)
$$

$$
\tilde{H}^{(N)}_S = \text{LN}(\text{FFN}(H_{IS}) + H^{(N)}_S)
$$

### SLU Decoder

For the intent detection, we follow Kim (2014) to employ the maxpooling on $\tilde{H}^{(N)}_I$ to obtain $c$, which is used to predict the intent label: $o^I \sim \tilde{S}^I = \text{softmax} (W^I c + b_I)$.

For the slot filling, we apply a standard CRF layer (Niu et al., 2019) to model the dependency

| Model                          | SNIPS         | ATIS          |
|-------------------------------|---------------|---------------|
|                              | Slot (F1)     | Intent (Acc)  | Overall (Acc) | Slot (F1)     | Intent (Acc)  | Overall (Acc) |
| Stack-Propagation (Qin et al., 2019) | 94.20         | 98.00         | 86.90         | 95.90         | 96.90         | 86.50         |
| Co-Interactive (Qin et al., 2020)        | 95.35         | 98.71         | 89.12         | 95.47         | 97.65         | 86.69         |
| Graph-LSTM (Zhang et al., 2020)        | 95.30         | 98.29         | 89.71         | 95.91         | 97.20         | 87.57         |
| Baseline (BiLSTM+Decoder)        | 94.19         | 97.79         | 85.86         | 95.32         | 95.63         | 84.99         |
| * (Label attention-shallow concat) | 94.39         | 98.03         | 87.89         | 95.55         | 97.52         | 85.89         |
| + Conventional Attention (1st order based model) | 95.37         | 98.34         | 88.12         | 95.64         | 97.43         | 87.01         |
| + Bilinear attention block     | 95.35         | 98.43         | 88.57         | 95.83         | 97.43         | 87.32         |
| + Dynamic Feature Fusion       | 95.57         | 98.57         | 89.43         | 95.88         | 97.56         | 87.57         |
| + ELU                          | 96.01         | 98.69         | 90.43         | 95.95         | 97.89         | 88.12         |
| HAN (Ours)                     | 96.18         | 99.12         | 91.80         | 96.12         | 98.04         | 88.47         |
| HAN w/ BERT                    | 97.66         | 99.23         | 93.54         | 96.83         | 98.54         | 89.31         |

Table 2: Performance of different model on the SNIPS and ATIS datasets. Our HAN achieves the state-of-the-art performance on the two benchmark datasets.
between labels, and then predict the label sequence $P(y_t|O_S) = \sum_{y'_t} \sum_{s=1}^{N} \exp(f(y'_{t-1}, y'_t, O_S))$, where $f(y'_{t-1}, y'_t, O_S)$ computes the transition score from $y_{t-1}$ to $y_t$ and $O_S = W^S\hat{H}_S^{(N)} + b_S$.

3 Experiments

Main Results Table 2 shows the results of our approach on the SNIPS and ATIS, our HAN outperforms all baselines and achieves the state-of-the-art performance. Besides, fine-tuned with the strong pre-trained language model (BERT) (Devlin et al., 2019) , HAN has been further improved. For the ablation study, we can see that as adding each key component of the model gradually, the performance gradually becomes better, and it gets improvement when equipping with ELU (4.57% and 3.13% improvement compared to baseline in overall accuracy on the SNIPS and ATIS dataset, respectively). The "shallow concat" means directly concatenate the two features without dynamic feature fusion mentioned above.

Robustness towards Learning Rate From Figure 3, with the overall Accuracy as metric, we show that under same experimental settings, infinity order SLU model performs better than the first order model under different learning rate. Besides, we find that under reasonable and task-specific range of the learning rate, i.e., 1e-4 to 1e-2, the higher-order based model performs slightly and consistently better than the 1st order based model. While when the learning rate is out of this range, i.e., bigger than 1e-2 or smaller than 1e-4, the performance of the 1st order based model occurs to crack down quickly and it even drops to 0 when the learning rate is 0.1. Oppositely, the higher-order based model, though also drops down when the learning reaches is set out of reasonable range, can still keep considerable performance compared to the first order base model, and thus shows its robustness to the extreme case towards the optimized learning rate. A similar phenomenon also can be found on the ATIS dataset (please see our Appendix).

Generalization Analysis We attempt to incorporate the Higher-order Attention Encoder (marked as HAE) into several existing baselines. Table 3 shows that baselines with infinity order attention, i.e., HAE, performs better than it with 1st order attention model in most of the case. This further verifies the generalization of the effectiveness of the higher-order attention on the SLU task.

Visualization of the Infinity Order Attention To explore the model promotion brought from the proposed HAN, we turn to visualize the attention pattern over Q and K in Eq. (5). As can be seen in Figure 4, where we use the utterance "What film is playing nearby" from the SNIPS dataset, the proposed higher-order attention model shows clearer attention capture ability compared to the original 1st attention mechanism, it can better focus on the keyword film and nearby.

4 Conclusion

In this paper, we propose a novel Bilinear attention block which can build the 2nd order interactions between intent and slot features and get more dis-
criminative intent and slot representations. The higher and even infinity order feature interactions can be readily modeled via stacking multiple Bi-Linear attention blocks and equipping the block with ELU activation. Moreover, we introduced the HAN, and conducted numerous experiments and analysis on SNIPS and ATIS datasets to demonstrate the effectiveness of our method.

A Related Work

A.1 Spoken Language Understanding

Spoken Language Understanding is a well-known task in dialogue system, and it typically contains intent detection and slot filling tasks. The special relation of the two tasks requires them to have enough correlation and interaction, making it possible to explore the promotion brought from higher order attention.

A.2 Bilinear Pooling

Bilinear pooling was first proposed in (Lin et al., 2015) to fuse the features for fine-grained visual recognition, it can provide 2nd order interaction on feature vectors. Later for the SLU task, Teng et al. (2020) proposed to use Bilinear pooling to fuse the word information and character information, showing that such method can provide more discriminative representations than simple pooling, i.e., 1st order, for the spoken language understanding task.

B Experimental Details

B.1 Experimental Settings

We adopt the RAdam (Liu et al., 2019a) optimizer for optimizing the parameters, with a mini-batch size of 32 and initial learning rate of 0.001. We use 300d GloVe pre-trained vector (Pennington et al., 2014) as the initialization embedding. The hidden dimensionality is set as 128. Two evaluation metrics are used in the SLU task. The performance of intent detection is measured by accuracy, while slot filling is evaluated with the F1 score, and the sentence-level semantic frame parsing using overall accuracy.

C More Experiment Results

C.1 Learning Rate on ATIS

Besides the performance of the higher order model and the first order model in the SNIPS dataset w.r.t, learning rate in Section 3, we also show the results in the ATIS dataset. From Figure 5, we can see that the higher order attention based model performs better than the first order based model consistently, and it shows a clear robustness towards the learning rate for its adaptive capacity in the hyper-parameter.

C.2 Discussion on the layer number of Higher-order Attention Encoder

From Table 4, we can see that when the number of sublayers in Higher-order Attention Encoder is 2, performance of HAN on both validation dataset gets the best. So we set the number of sublayers N = 2. We speculate that the increased parameters by stacking more blocks might result in overfitting, which somewhat hinders the exploitation of higher order interaction in this way.

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