AWTE-BERT: Attending to Wordpiece Tokenization Explicitly on BERT for Joint Intent Classification and Slot Filling

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Abstract

Intent classification and slot filling are two core tasks in natural language understanding (NLU). The interaction nature of the two tasks makes the joint models often outperform the single designs. One of the promising solutions, called BERT (Bidirectional Encoder Representations from Transformers), achieves the joint optimization of the two tasks. BERT adopts the wordpiece to tokenize each input token into multiple sub-tokens, which causes a mismatch between the tokens’ and the labels’ lengths. Previous methods utilize the hidden states corresponding to the first sub-token as input to the classifier, which limits performance improvement since some hidden semantic informations is discarded in the fine-tune process. To address this issue, we propose a novel joint model based on BERT, which explicitly models the multiple sub-tokens features after wordpiece tokenization, thereby generating the context features that contribute to slot filling. Specifically, we encode the hidden states corresponding to multiple sub-tokens into a context vector via the attention mechanism. Then, we feed each context vector into the slot filling encoder, which preserves the integrity of the sentence. Experimental results demonstrate that our proposed model achieves significant improvement on intent classification accuracy, slot filling F1, and sentence-level semantic frame ac-

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accuracy on two public benchmark datasets. The F1 score of the slot filling in particular has been improved from 96.1 to 98.2 (2.1% absolute) on the ATIS dataset.

**Keywords:** Wordpiece, Intent Classification, Slot Filling, BERT, Attention Mechanisms

1. **Introduction**

In recent years, with the rapid development of artificial intelligence technology, various intelligent voice assistants have achieved great success and entered one’s life. Natural language understanding (NLU) is a core part of intelligent voice assistants. One of the goals of NLU is to create a structured framework for user queries, usually consisting of two tasks: intent classification and slot filling [Tur and De Mori 2011, Tur and Deng 2011]. Intent classification can be seen as a classification problem, which classifies speakers intent and slot filling can be treated as a sequence labeling task, which predicts the slot label sequence. Take a query utterance as an example, “I want a flight round trip from Memphis to Seattle on June thirtieth”, as shown in Table 1. Table 1 shows that each word in an utterance has a different slot label with a specific intent for the entire utterance, the intent is atis-flight, the "round" is B-trip, the "trip" is I-trip, the "Memphis" is B-cityname, the "Seattle" is B-cityname, the "June" is B-day, and the "thirtieth" is I-day.

Table 1: An example utterance with intent and slot annotation form ATIS (Hemphill et al., 1990) dataset in IOB format (B is the beginning of entity, I is mid and end of entity, and O is not the entity). After Wordpiece tokenization, 'thirtieth' is split to ['th', '##ir', '##tie', '##th'].

| Query | I want a flight round trip from Memphis to Seattle on June thirtieth |
|-------|---------------------------------------------------------------------|
| Wordpiece tokenization | I want a flight round trip from Memphis to Seattle on June th ##ir ##tie ##th |
| Slot Filling | I | O | O | O | B-trip | I-trip | O | B-cityname | O | B-cityname | O | B-day | I-day |
| Intent Classification | atis-flight |

Previous approaches show that intent classification and slot filling are implemented separately. Intent classification can be seen as a classification problem to predict the intent label $y_i$. Slot filling can be treated as a sequence labeling task that maps
an input word sequence \( x = (x_1, \ldots, x_T) \) to the corresponding slot label sequence \( y^S = (y^S_1, \ldots, y^S_T) \). The early intent classification and slot filling relied heavily on rules (Ramanand et al., 2010). Then, machine learning has been introduced to intention classification, such as support vector machine (SVM) (Schuurmans and Frasincar, 2019). As deep learning models become more diverse and mature, recurrent neural network (RNN) based approaches, particularly gated recurrent unit (GRU) and long short-term memory (LSTM) models help intent classification and slot filling achieved state-of-the-art performance (Goo et al., 2018; Guo et al., 2014; Hakkani-Tür et al., 2016). Recently, many pretraining techniques, particularly Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2018) has been widely used in NLP tasks and has created state-of-the-art models on specific datas. Since then, (Chen et al., 2019) propose a joint BERT model which uses a pre-training model to encode sentence semantics information, and then applies for the tasks of intent classification and slot filling.

Despite the joint BERT model being an effective strategy for joint intent classification and slot filling, it always suffers from loss of sentence semantics information issue. A complex word is tokenized into sub-words for wordpiece tokenization, for example, 'Thirtieth' is tokenized into ['th', '##ir', '##tie', '##th'], as shown in Table 1. Thus, for slot filling task, the lengths of tokens are not equal to the lengths of labels, which leads to the inevitable loss of sentence semantics information and a decrease in the performance of the joint model. (Chen et al., 2019) feeds each input token into a wordpiece tokenizer and uses the hidden state corresponding to the first sub-token as input to the softmax classifier. (Yang et al., 2021) introduces a position-aware multi-head masked attention (PMMAtt) mechanism as slot decoder, also only use the hidden state corresponding to the first sub-token as input to the slot decoder. However, those approaches still lose some sub-words hidden states information and fail to take advantage of the complete sentence information.

To address this challenge, we propose a novel model for joint intent classification and slot filling by adopting the wordpiece tokenization attention (WTAtt) mechanism, which explicitly models the multiple sub-tokens features. As illustrated in Figure 2, our model first encodes shared hidden information for intent classification and slot fill-
ing via BERT layer. After that, to utilize all sub-words in a sentence after wordpiece tokenization, we adopt the wordpiece tokenization attention (WTAtt) mechanism to solve each sub-words information which illustrated in Figure 2 (b). In the wordpiece tokenization attention (WTAtt) mechanism, we apply the self-attention layer to extract word information in each complex sub-word. Finally, we leverage a linear layer as intent classification decoder and the CRF (Raymond and Riccardi, 2007) as slot filling decoder. Compared to the previous BERT-based model, our model obviously can capture associations between sub-words, providing more sentence features for slot filling task. Since the proposed model Attends to Wordpiece Tokenization Explicitly on BERT, we name it AWTE-BERT. Figure 1 shows the difference between the BERT-based model and our proposed AWTE-BERT for an example of slot filling.

![Figure 1: The difference between the conventional BERT-based model (Chen et al., 2019; Yang et al., 2021) and the AWTE-BERT for an example of slot filling. The BERT-based model losses some sub-words hidden information, our model takes advantage of the complete sentence information via the WTAtt mechanism.](image)

The experimental results on benchmark datasets including ATIS (Hemphill et al., 1990) and Snips (Coucke et al., 2018) show that our model achieves significant improvement as compared to all baseline methods. In particular, we show that the slot filling performance has been significantly improved, this is probably due to the slot filling relying on complete sentences, our model can learn more features. In summary, the main contributions in this work are three folds:
1. To the best of our knowledge, we are the first to analyze the wordpiece tokenization issue on BERT. We propose a novel model for joint intent classification and slot filling via the WTAtt mechanism, which can explicitly model the multiple sub-tokens features.

2. We analyze the effect of the WTAtt mechanism on the overall performance and conduct extensive experiments to demonstrate the proposed model. The visualization of the learned weights illustrates the interpretability of our model.

3. The experiments on two SLU datasets (ATIS and Snips) show the proposed model which achieves significant improvement in intent classification accuracy, slot filling F1, and sentence-level semantic frame accuracy compared to previous state-of-the-art models.

The rest of this paper is organized as follows: In Section 2, related work is presented. It demonstrates how our work differs from existing research. In Section 3, the architecture of our model is introduced. Section 4 discusses the experimental datasets, training details, baselines, evaluation results, ablation analysis and case study. Finally, the discussion is followed by the conclusions of our research work in Section 5.

2. Related work

In this section, we introduce some previous works in NLU, including intent classification, slot filling and the joint model.

2.1. Intent Classification

Intent classification can be formulated as an utterance classification problem. Many machine learning methods like support vector machine (SVM) (Schuurmans and Frasincar, 2019) can be applied for text classification. As a text classification task, the performance of intent classification depends on the order of each word in the sentence. Traditional machine learning methods find it difficult to capture sequence information, limiting the model performance. Deep learning models have been extensively explored in intent classification. Convolutional neural networks (CNN) was employed for detecting the intents of a user search query. The author of Kim (2014) report a simple
CNN with little hyperparameter tuning and static vectors achieves excellent results on multiple benchmarks, which is learning task-specific vectors through fine-tuning offers further gains in performance. Zhang et al. (2015) offers an empirical exploration on the use of character-level convolutional networks (ConvNets) for text classification. Then, RNN and LSTM have also been widely used in intent classification tasks. Ravuri and Stolcke (2015) propose RNN and LSTM models for utterance classification. Zhao and Wu (2016; Yang et al., 2016) used an attention-based model for intent detection.

However, the method that we proposed model for intent classification is different from the previous works. We propose a novel joint model that models intent features into slot decoder explicitly. Also, the information shared by the two tasks helps in improving the performance of each task in comparison to the tasks being done individually.

2.2. Slot Filling

Slot filling can be treated as a sequence labeling task. The traditional method uses probabilistic models such as HMM, MEMM (McCallum et al., 2000), and CRF (Raymond and Riccardi, 2007) to solve the task. With the development of deep learning, models based on deep learning are used for sequence labeling tasks, and their performance has surpassed the methods based on traditional machine learning. Convolutional neural networks (CNN) (Vu, 2016) was proposed to solve the sequence labeling task in spoken language understanding. Many based-RNN models become the popular approaches for sequence labeling, such as LSTM and RNN. For the word labeling task, Yao et al. (2014) investigates using LSTM to apply to the task. Peng et al. (2015) propose to use external memory to improve memorisation capability of RNNs. Kurata et al. (2016) first enhance LSTM-based sequence labeling to explicitly model label dependencies. Zhao and Feng (2018) introduced the seq2seq model for sequential labeling.

The difference between these methods and our method is that we introduced the WTAtt mechanism to learn feature between sub-tokens for complex words.
2.3. Joint Model

In consideration of the high correlation between intent classification and slot filling, the tendency is to develop a joint model for intent classification and slot filling tasks. Many models implicitly learn the information of feature between intent classification and slot filling tasks by sharing parameters. And then, many methods explicitly feed intent information to the slot filling model, other methods aim to model the bi-directional interrelationship between the intent and slot. The author in (Liu and Lane, 2016) propose an attention-based neural network model for joint intent detection and slot filling, such attentions provide additional information to the intent classification and slot label prediction. Goo et al. (2018) used a slot-gated mechanism that applies intent information to guide the slot filling, which captures the relationship between the intent and slot attention vectors. (Zhang et al., 2020) tackles this task with the Graph LSTM model, which not only addresses the limitations of sequential models but can also help to utilize the semantic correlation between slot and intent. Many models based Transformer structures were employed for intent detection and slot filling. Qin et al. (2021a) propose a Co-Interactive Transformer that considers the cross-impact between the two tasks, which slot and intent can be able to attend on the corresponding mutual information. Wang et al. (2021) propose a Transformer encoder-based architecture with syntactical knowledge encoded for intent detection and slot filling, which predict syntactic parse ancestors and part-of-speech of each token via multi-task learning. Ding et al. (2021) propose a Dynamic Graph Model for joint multiple intent detection and slot filling in which we adopt a sentence-level intent-slot interactive graph to model the correlation between the intents and slot, which can dynamically update the interactive graph and further alleviate the error propagation.

Recently, a variety of techniques were proposed for training general purpose language representation models using an enormous amount of unannotated text to address the data sparsity challenge, such as BERT (Devlin et al., 2018), ELMo (Peters et al., 2018) and Generative Pre-trained Transformer (GPT) (Radford et al., 2018). Chen et al. (2019) introduce a joint intent classification and slot filling model based on BERT. Qin et al. (2019) adopt a joint model with StackPropagation for NLU to directly use the intent information as input for slot filling, thus to capture the intent semantic knowl-

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edge, which further guides the slot filling. Also, the author in (Qin et al., 2019) use the BERT model in our framework, which further boosts the performance of the NLU task.

However, most of them still lack solutions for sub-tokens after wordpiece tokenization. Compared to early works, our work is the first to leverage the attention mechanism to address wordpiece tokenization in BERT-based models for intent classification and slot filling.

3. Proposed Method

In this section, we will introduce the AWTM-BERT for joint intent classification and slot filling, which consists of the BERT encoder layer, the wordpiece tokenization attention (WTAtt) mechanism and two decoders. First, the BERT encoder layer (Section 3.1) encodes an utterance to obtain the shared information between intent classification and slot filling. Then, the intent classifier decoder performs intent classification. Furthermore, the wordpiece tokenization attention (WTAtt) mechanism (Section 3.2) leverages the self-attention layer to construct multiple sub-words complex word semantics information, which keeps sentence information complete. Finally, we use CRF as slot filling decoder. Both intent classification and slot filling are optimized via a joint learning model (Section 3.3). The architecture of model is illustrated in Figure 2.

3.1. Bert Encoder Layer

The model architecture of BERT (Devlin et al., 2018) is a multi-layer bidirectional Transformer encoder based on the Transformer model. The input of the model is a concatenation of WordPiece embeddings, positional embeddings, and the segment embedding. The pre-trained BERT model provides a strong context-related sentence representation and can be used for a variety of target tasks. For text classification task, the BERT model insert a special embedding ([CLS]) as the first token, and the output vector corresponding to the token is used as the semantic representation of the sentence. For sequence labeling task, The BERT model uses the output vector corresponding to each word in the sentence to predict the label. Therefore, BERT can easily be expanded
Figure 2: Illustration of our WTME-BERT model for joint intent classification and slot filling. It consists of the BERT layer, wordpiece tokenization attention mechanism, and two decoders. (b) is the wordpiece tokenization attention mechanism. It leverages the self-attention layer to construct sentence semantics information for sub-words and uses CRF as slot filling decoder.

to a joint intention classification and slot filling model. In this paper, given an input token sequence \( x = (x_1, \ldots, x_T) \), the output of BERT is \( H = (h_1, \ldots, h_T) \).

For intent classification, which based on the hidden state (denoted \( h_1 \)) of the first special token ([CLS]), the intent \( y^i \) is predicted as:

\[
y^i = \text{softmax}(W^i h_1 + b^i),
\]

where \( W^i \) is the weight matrix and \( b^i \) is the bias.

For slot filling, \( x \) is mapping to its corresponding slot label sequence \( y = (y^S_1, \ldots, y^S_T) \). The BERT-based model usually feeds the final hidden states of other tokens \( (h_2, \ldots, h_T) \) into a softmax layer to classify over the slot filling labels. To make this process compatible with the WordPiece tokenization, the BERT-based model input each tokenized input word into the WordPiece tokenizer and use the hidden state corresponding
to the first sub-token as input to the softmax classifier.

Therefore in the previous BERT-based model, the hidden states of subsequent sub-
token for complex words is discarded which can loss the sentence semantics informa-
tion. The attention-based WordPiece tokenization module is primarily designed to
address this issue.

3.2. Wordpiece Tokenization Attention Mechanism

This part describes the proposed attention-based WordPiece tokenization module
illustrated in Figure 2 (b). For slot filling task, the module adds a self-attention layer to
address sub-tokens. This attention mechanism utilizes all semantics information of the
complex words, keeping complete sentence semantics information, in order to improve
slot filling performance.

Figure 1 shows that ‘thirtieth’ is mapping to (‘th’, ‘##ir’, ‘##tie’, ‘##th’) based on
the WordPiece tokenization. For each complex word, we get sub-words hidden states
by the BERT encoder layer. For each sub-word hidden states, we compute the slot
context vector \( s_i \) as the weighted sum of the complex word information, by the learned
attention weights \( \alpha_{i,j} \):

\[
s_i = \sum_{j=1}^{T} \alpha_{i,j} h_j ,
\]

where the slot attention weights are computed as below.

\[
\alpha_{i,j} = \frac{\exp(e_{i,j})}{\sum_{k=1}^{T} \exp(e_{i,k})} ,
\]

\[
e_{i,k} = \sigma(W_{he} h_k) ,
\]

where \( \sigma \) is the activation function, and \( W_{he} \) is the weight matrix. Then the hidden state
and the slot context vector are utilized for slot filling. Since slot label predictions are
dependent on predictions for surrounding words, here we use the CRF (Raymond and
Riccardi 2007) for slot filling label decoder. In addition, considering intent informa-
tion is beneficial for slot filling, we feed \( s_i \) together with \( h_1 \) into slot filling decoder,
where $s_i$ is the slot context vector of the i-th word after the WTAtt layer, and $h_1$ is the hidden state of the [CLS].

3.3. Joint Optimization

To obtain both slot filling and intent classification prediction jointly, the objective is formulated as:

$$p(y^S, y^I | X) = p(y^I | X) \prod_{t=1}^{T} p(y^S_t | X)$$

$$= p(y^I | x_1, \cdots, x_T) \prod_{t=1}^{T} p(y^S_t | x_1, \cdots, x_T)$$

where $p(y^S, y^I | X)$ is the conditional probability of the understanding result (slot filling and intent classification) given the input word sequence and is maximized.

4. Experiments and Analysis

4.1. Dataset

We will experiment in the most wildly used NLU datasets, which are ATIS (Hemphill et al., 1990) and SNIPS (Coucke et al., 2018). Both ATIS and SNIPS are English datasets, ATIS only about flight information. SNIPS is more complicated than ATIS, contains weather, ordering restaurants, and playing music. Table 2 shows the datasets segmentation and labeling details for ATIS and SNIPS. In the following, we will give a detailed description.

ATIS (Airline Travel Information Systems): ATIS dataset contains audio recordings of flights and reservations. There are 4478 utterances for training, 893 utterances for validation, and 500 utterances for testing. 120 slot labels and 21 intent types are included in ATIS training data. The number of sub-words in the whole dataset is 1597.

SNIPS: SNIPS is the custom-intent-engines collected by Snips voice assister. There are 13,084 utterances for training, 700 utterances for validation, and 700 utterances for testing. There are 72 slot labels and 7 intent types. The number of sub-words in the whole dataset is 10511.
Table 2: Datasets segmentation and labeling details for ATIS and Snips

| Dataset              | ATIS   | Snips  |
|----------------------|--------|--------|
| Vocabulary Size      | 11241  | 722    |
| Average Sentence Length | 9.05   | 11.28  |
| Sub-words Number     | 1597   | 10511  |
| #Training Set Size   | 4478   | 13084  |
| #Validation Set Size | 500    | 700    |
| #Testing Set Size    | 893    | 700    |
| #Slot labels         | 120    | 72     |
| #Intents             | 21     | 7      |

4.2. Training Details

Table 3 shows the hyper-parameters setting used in this experiment. Our model employs the English uncased Bert-Base model (Devlin et al., 2018) as pre-model, which has 12 layers, 768 hidden states, and 12 heads. For fine-tuning, all hyper-parameters are tuned on the validation datasets. The attention mechanism hidden states are 768. The batch size is 256. AdamW (Kingma and Ba, 2014) is used for optimization with a learning rate of 5e-5. The dropout probability is 0.1. The maximum number of epochs is selected from [10, 30, 40, 50, 60, 80]. Experiments are conducted on GeForce RTX 3090.

4.3. Baselines

We compare our model with the existing baselines, these baselines can be classified into three categories: (Liu and Lane, 2016) is the implicit joint model; (Goo et al., 2018; Zhang et al., 2020; Qin et al., 2021a; Wang et al., 2021; Ding et al., 2021) are the explicit joint model; (Chen et al., 2019; Qin et al., 2019) are the pre-train model. All results are obtained on the same datasets.

The implicit joint model:
Table 3: Hyper-parameters of experiments.

| Layer             | Hyper-parameter | Size |
|-------------------|-----------------|------|
| BERT Embedding    | Dimension       | 768  |
|                   | Layers          | 12   |
|                   | Heads           | 12   |
| Attention         | Hidden states   | 768  |
| Dropout           | Dropout rate    | 0.1  |
| Batch size        |                 | 256  |
| Number of epochs  |                 | 30   |
| Learning rate     |                 | 5e-5 |

- **Attention BiRNN** ([Liu and Lane, 2016](#)) proposes a sequence-to-sequence model with the attention mechanism. The model allows the network to learn the relationship between slot and intent.

**The explicit joint model:**

- **Slot-Gated Atten** ([Goo et al., 2018](#)) proposes the slot-gated joint model to explore the correlation of slot filling and intent detection better, which utilizes intent information for slot filling through the slot-gated mechanism.

- **Graph LSTM** ([Zhang et al., 2020](#)) adopts the Graph LSTM model to convert text into a graph and then utilizes the message passing mechanism to learn the node representation which makes better use of context information for slot filling.

- **Co-Interactive transformer** ([Qin et al., 2021a](#)) employs a Co-Interactive Transformer which considers the cross-impact between intent classification and slot filling.

- **SyntacticTF** ([Wang et al., 2021](#)) utilizes a novel Transformer encoder-based ar-
achitecture with syntactical knowledge encoded for intent detection and slot fill-
ing.

• **DGM (Ding et al. 2021)** has shown that a Dynamic Graph Model (DGM) for joint multiple intent detection and slot filling, in which we adopt a sentence-level intent-slot interactive graph to model the correlation between the intents and slot.

*The pre-training model:*

• **Joint BERT (Chen et al. 2019)** first uses the BERT model to explore joint slot filling and intents classification. The pre-trained BERT model provides a powerful context-dependent sentence representation.

• **Stack-Propagation + BERT (Qin et al. 2019)** introduces a joint model with Stack-Propagation to directly use the intent information as input for slot filling which captures the intent semantic knowledge.

### 4.4. Experimental results

Referring to previous works, we evaluate the NLU performance about slot filling using F1 score, intent classification using accuracy, and sentence level semantic frame parsing using overall accuracy, which is the proportion of sentences with slots and intent are both correctly predicted in the whole dataset. We choose the model that performs best on the validation set and then evaluate the results on the test set. Table 4 shows the experiment results of the proposed models on intent classification and slot filling compared to the previous state-of-the-art models.

From the table, the first model is the baseline of the implicit joint model, the second group of models is the baseline of the explicit joint model, the third group of models is the pre-training model and they consist of the state-of-the-art joint intent classification and slot filling models. The last group of models is the proposed AWTM-BERT model. We can see that our model significantly outperforms all the baselines for slot filling task by a large margin and achieves state-of-the-art performance.

In ATIS dataset, the AWTM-BERT model achieves slot filling F1 of 98.2% (from 96.1%), and sentence-level semantic frame accuracy of 90.1% (from 88.6%). In another Snips dataset, the AWTM-BERT achieves intent accuracy of 99.1% (from 99.0%),
and slot filling F1 of 97.8% (from 97.0%). These results demonstrate the effectiveness of our AWTM-BERT model. The experimental results show that the slot filling task has been significantly improved. We attribute the improvement to the following reasons:

- The proposed model can select effective features for slot filling with the WTAtt mechanism, further improving the overall performance.
- Compared to intent classification task, slot filling task gets a large margin. This is probably due to the slot filling relying on complete sentences, our model can learn more features.

Table 4: NLU performance on Snips and ATIS datasets. The metrics are intent classification accuracy, slot filling F1, and sentence-level semantic frame accuracy. The results for the baselines are mainly cited from (Qin et al., 2021b). For the SyntacticTF(Independent) and the DGM, we adopt the results reported by Wang et al., 2021 and Ding et al., 2021.

| Models                             | ATIS   | SNIPS  |
|-----------------------------------|--------|--------|
| Intent Acc | Slot F1 | Overall Acc | Intent Acc | Slot F1 | Overall Acc |
| Attention BiRNN (Liu and Lane, 2016) | 91.1   | 94.2   | 78.9       | 96.7   | 87.8   | 74.1       |
| Slot-Gated Full Attention (Goo et al., 2018) | 93.6   | 94.8   | 82.2       | 97.0   | 88.8   | 75.5       |
| Graph LSTM (Zhang et al., 2020)      | 97.2   | 95.9   | 87.5       | 98.2   | 95.3   | 89.7       |
| Co-Interactive Transformer (Qin et al., 2021a) | 97.7   | 95.9   | 87.4       | 98.8   | 95.9   | 90.3       |
| SyntacticTF (Independent) (Wang et al., 2021) | 98.1   | 95.9   | -          | 98.7   | 96.5   | -          |
| DGM (Ding et al., 2021)              | 97.4   | 96.1   | 87.8       | 98.2   | 85.2   | 88.4       |
| Joint BERT (Chen et al., 2019)       | 92.8   | 95.7   | 88.2       | 99.0   | 96.2   | 91.6       |
| Stack-Propagation+BERT (Qin et al., 2019) | 97.5   | 96.1   | 88.6       | 99.0   | 97.0   | 92.9       |
| AWTM-BERT                           | 98.1   | 98.2   | 90.1       | 99.1   | 97.8   | 92.1       |

5. Experimental Analysis

In this section, we analyze the major components’ effectiveness of our proposed model and conduct an ablation analysis. For the WTAtt mechanism, we conduct experiments to illustrate its effectiveness. Then, we adopt ablation analysis, model result analysis, and case study to demonstrate our model effectively. In addition, the learning results of the WTAtt mechanism are visualized to demonstrate its interpretability.
5.1. Effect of Wordpiece Tokenization Attention Mechanism for Slot Filling

We introduce the wordpiece tokenization attention (WTAtt) mechanism to capture the sub-tokens for complex words in the sentence. To evaluate the effect of the WTAtt mechanism, we only train the proposed AWTE-BERT model for slot filling task. We conduct the experiments with the following ablation:

- w/o the intent classification task, only train for slot filling task, where the slot decoder does not rely on the output of the intent information, and only feed hidden states after the WTAtt mechanism layer into the slot decoder.

As shown in the AWTE-BERT (for slot) row in Table 5, we find that the slot filling performance is further improved, which also demonstrates that the wordpiece tokenization attention mechanism is beneficial for slot filling. It is observed that slot filling models perform well without intent classification task with 0.5% and 0.2% improvement relative to the AWTE-BERT model on the ATIS and SNIPS datasets, respectively.

5.2. Ablation Analysis

To evaluate the effectiveness of the intent feature, the WTAtt mechanism, and the CRF layer in the proposed model, we conduct the experiments with the following ablations:

- w/o the intent feature, where the slot decoder does not rely on the output of the intent classifier, and only feed hidden states after the WTAtt layer into slot decoder.

- w/o the WTAtt mechanism, where the WTAtt mechanism is removed, and the hidden states corresponding to the first sub-token of BERT is used to predict each slot.

- w/o the CRF layer, where the slot decoder replaces the CRF layer with the softmax classifier, the slot is predicted as:

\[ y_i^S = \text{softmax}(W_{hy}^S(h_i + s_i)) \]  \hspace{1cm} (6)
where $y_i^S$ is the slot label of the $i$-th word in the input, $W_{h_y}^S$ is the weight matrix, $s_i$ is the slot context vector of the $i$-th word after the WTAtt layer, and $h_1$ is the hidden state of the [CLS].

Table 5 shows the performance of our joint model on ATIS and SNIPS obtained after removing one or more components or features at a time. It is observed that each component or feature contributes to the overall performance.

If we remove the intent feature, we find that the intent accuracy almost the same as the AWTE-BERT results, but the slot F1 and overall accuracy decrease on both datasets. These results show that the intent information is beneficial for slot filling.

If we remove the WTAtt mechanism, we see from Table 4 that the performance on both datasets decreases dramatically. The slot F1 and overall accuracy drop by 5.4% and 8.8% on ATIS and decrease 2.2% and 2.1% on SNIPS. The results further demonstrate the effectiveness of the proposed the WTAtt mechanism, which can better capture the sub-tokens information between complex word to guide the slot filling and improve the overall performance.

If we remove the CRF layer which the replaces with the softmax classifier, we see the slot F1 and overall accuracy decrease on both datasets. Experiments show CRF layer has a positive effect on model performance. This is probably due to the CRF layer can obtain the possible tag sequences at the sentence level. The CRF mainly focuses on sequence labeling which has a positive effect for slot filling.

Table 5: Ablation analysis. The first group is the result of Section 5.1. The second group is the result of Section 5.2. The third group is the result of the AWTE-BERT.

| Models                     | ATIS       | SNIPS       |
|----------------------------|------------|-------------|
|                            | Intent Acc | Slot F1     | Overall Acc | Intent Acc | Slot F1 | Overall Acc |
| AWTE-BERT (for slot)       |            | 98.7        |             |            | 98.0    |             |
| w/o intent feature         | 97.8       | 97.9        | 88.4        | 98.7       | 97.6    | 91.0        |
| w/o WTAtt mechanism        | 97.5       | 92.8        | 81.3        | 98.2       | 95.6    | 90.0        |
| w/o CRF layer              | 98.0       | 97.0        | 88.0        | 98.8       | 97.0    | 90.4        |
| AWTE-BERT                  | 98.1       | 98.2        | 90.1        | 99.1       | 97.8    | 92.1        |
5.3. Model Result Analysis

To select the best set of results on ATIS and SNIPS, we compare the AWTM-BERT model with different fine-tuning epochs. Figure 3 show that the best effect of the intent acc is 98.1% and the slot F1 is 98.2% by epoch 60 on ATIS. And on SNIPS is 99.1% and 97.8% by epoch 40 in figure 3(b).

Figure 3: The different epochs analysis on ATIS (a) and SNIPS (b). X-axis is the different epochs and Y-axis is the score of intent acc and slot f1.
5.4. Case Study

To compare our proposed model and other based-BERT models, we select a case from ATIS, as in Table 6. The AWTM-BERT outperforms the joint BERT model \cite{chen2019joint} by capturing the sub-tokens information of the WTAtt mechanism to improve the generalization capability. In this case, “june thirtieth” is wrongly predicted by the joint BERT model as an un-slot. However, the AWTM-BERT correctly predicts the slot labels because “june thirtieth” is a complex word and the WTAtt mechanism worked well.

Table 6: A cases in the ATIS dataset. The slots of “june” and “thirtieth” is “B-depart\_date.month\_name” and “B-depart\_date.day\_number”, which the green part is wrongly predicted by the AWTM-BERT model, and the red part is error predicted by the joint BERT model.

| Query | what is the earliest flight from memphis to cincinnati on june thirtieth |
|-------|------------------------------------------------------------------------|
| Wordpiece | \textquote{what,\ times,\ the,\ earliest,\ flight,\ from,\ memphis,\ to,\ cincinnati,\ on,\ june,\ \#th,\ \#th,\ \#th} |
| Correctly, predicted by the AWTM-BERT | \textquote{atis\_flight} |
| Slots | \textquote{O O B-flight\_mod O O B-from\_city\_name O B-to\_city\_name O B-depart\_date.month\_name B-depart\_date.day\_number} |
| Predicted by the joint BERT \cite{chen2019joint} | \textquote{atis\_flight} |
| Slots | \textquote{O O B-flight\_mod O O B-from\_city\_name O B-to\_city\_name O O O} |

5.5. Visualization

To better understand what the proposed model has learned, we visualized subwords attention weights of the WTAtt mechanism, which is shown in Figure 4. Based on the complex words “thirtieth” and “redbreast” and the slots “I-day” and “I-track”, we can observe that the attention weights successfully focus on the complete sub-tokens, which means complete sub-tokens information is playing an important role in slot filling. This indicates that the proposed wordpiece tokenization attention mechanism can help our model construct complete sentence semantics information.
6. Conclusion and Future Work

In this paper, we propose a novel joint model based on BERT which explicitly models the multiple sub-tokens features after wordpiece tokenization for intent classification and slot filling. Designed to solve the problem of wordpiece tokenization which the length of tokens is not equal to the length of labels for slot filling task. Also, we must consider label dependency and employ CRF as the slot filling decoder of our approach. Experiments show that our proposed approach outperforms the early model, demonstrating the efficacy of exploiting all the WordPiece tokenization sub-words for sequence labeling. Our proposed AWTM-BERT model gets significant improvement in intent classification accuracy, slot filling F1, and sentence-level semantic frame accuracy on ATIS and Snips datasets over previous state-of-the-art models. Finally, our approach is more useful for slot filling task, because the complete sub-tokens relations are stronger and easily modeled contextual information, and this paper provides the guidance of pre-model design for future sequence labeling tasks. In future work, we will generalize this model to more sequence labeling tasks and further model sub-token information.
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