

# BERT for Joint Intent Classification and Slot Filling

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## Abstract

Intent classification and slot filling are two essential tasks for natural language understanding. They often suffer from small-scale human-labeled training data, resulting in poor generalization capability, especially for rare words. Recently a new language representation model, BERT (Bidirectional Encoder Representations from Transformers), facilitates pre-training deep bidirectional representations on large-scale unlabeled corpora, and has created state-of-the-art models for a wide variety of natural language processing tasks after simple fine-tuning. However, there has not been much effort on exploring BERT for natural language understanding. In this work, we propose a joint intent classification and slot filling model based on BERT. Experimental results demonstrate that our proposed model achieves significant improvement on intent classification accuracy, slot filling F1, and sentence-level semantic frame accuracy on several public benchmark datasets, compared to the attention-based recurrent neural network models and slot-gated models.

## 1 Introduction

In recent years, a variety of smart speakers have been deployed and achieved great success, such as Google Home, Amazon Echo, Tmall Genie, which facilitate goal-oriented dialogues and help users to accomplish their tasks through voice interactions. Natural language understanding (NLU) is critical to the performance of goal-oriented spoken dialogue systems. NLU typically includes the intent classification and slot filling tasks, aiming to form a semantic parse for user utterances. Intent classification focuses on predicting the intent of the query, while slot filling extracts semantic concepts. Table 1 shows an example of intent classification and slot filling for user query “Find me a movie by Steven Spielberg”.

\*Ongoing work.

<b>Query</b>	Find me a movie by Steven Spielberg
<b>Frame</b>	<b>Intent</b> find_movie
	<b>Slot</b> genre = movie directed_by = Steven Spielberg

Table 1: An example from user query to semantic frame.

Intent classification is a classification problem that predicts the intent label  $y^i$  and slot filling is a sequence labeling task that tags the input word sequence  $x = (x_1, x_2, \dots, x_T)$  with the slot label sequence  $y^s = (y_1^s, y_2^s, \dots, y_T^s)$ . Recurrent neural network (RNN) based approaches, particularly gated recurrent unit (GRU) and long short-term memory (LSTM) models, have achieved state-of-the-art performance for intent classification and slot filling. Recently, several joint learning methods for intent classification and slot filling were proposed to exploit and model the dependencies between the two tasks and improve the performance over independent models (Guo et al., 2014; Hakkani-Tür et al., 2016; Liu and Lane, 2016; Goo et al., 2018). Prior work has shown that attention mechanism (Bahdanau et al., 2014) helps RNNs to deal with long-range dependencies. Hence, attention-based joint learning methods were proposed and achieved the state-of-the-art performance for joint intent classification and slot filling (Liu and Lane, 2016; Goo et al., 2018).

Lack of human-labeled data for NLU and other natural language processing (NLP) tasks results in poor generalization capability. To address the data sparsity challenge, a variety of techniques were proposed for training general purpose language representation models using an enormous amount of unannotated text, such as ELMo (Peters et al., 2018) and Generative Pre-trained Transformer (GPT) (Radford et al., 2018). Pre-trained models can be fine-tuned on NLP tasks and have achieved significant improvement over training on

task-specific annotated data. More recently, a pre-training technique, Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2018), was proposed and has created state-of-the-art models for a wide variety of NLP tasks, including question answering (SQuAD v1.1), natural language inference, and others.

However, there has not been much effort in exploring BERT for NLU. The technical contributions in this work are two folds: 1) we explore the BERT pre-trained model to address the poor generalization capability of NLU; 2) we propose a joint intent classification and slot filling model based on BERT and demonstrate that the proposed model achieves significant improvement on intent classification accuracy, slot filling F1, and sentence-level semantic frame accuracy on several public benchmark datasets, compared to attention-based RNN models and slot-gated models.

## 2 Related work

Deep learning models have been extensively explored in NLU. According to whether intent classification and slot filling are modeled separately or jointly, we categorize NLU models into independent modeling approaches and joint modeling approaches.

Approaches for intent classification include CNN (Kim, 2014; Zhang et al., 2015), LSTM (Ravuri and Stolcke, 2015), attention-based CNN (Zhao and Wu, 2016), hierarchical attention networks (Yang et al., 2016), adversarial multi-task learning (Liu et al., 2017), and others. Approaches for slot filling include CNN (Vu, 2016), deep LSTM (Yao et al., 2014), RNN-EM (Peng et al., 2015), encoder-labeler deep LSTM (Kurata et al., 2016), and joint pointer and attention (Zhao and Feng, 2018), among others.

Joint modeling approaches include CNN-CRF (Xu and Sarikaya, 2013), RecNN (Guo et al., 2014), joint RNN-LSTM (Hakkani-Tür et al., 2016), attention-based BiRNN (Liu and Lane, 2016), and slot-gated attention-based model (Goo et al., 2018).

## 3 Proposed Approach

We first briefly describe the BERT model (Devlin et al., 2018) and then introduce the proposed joint model based on BERT. Figure 1 illustrates a high-level view of the proposed model.

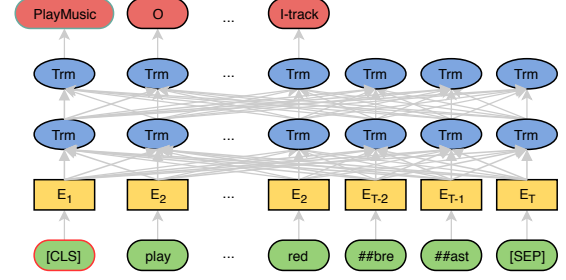


Figure 1: A high-level view of the proposed model. The input query is “play the song little robin redbreast”.

### 3.1 BERT

The model architecture of BERT is a multi-layer bidirectional Transformer encoder based on the original Transformer model (Vaswani et al., 2017). The input representation is a concatenation of WordPiece embeddings (Wu et al., 2016), positional embeddings, and the segment embedding. Specially, for single sentence classification and tagging tasks, the segment embedding has no discrimination. A special classification embedding ([CLS]) is inserted as the first token and a special token ([SEP]) is added as the final token. Given an input token sequence  $x = (x_1, \dots, x_T)$ , the output of BERT is  $H = (h_1, \dots, h_T)$ .

The BERT model is pre-trained with two strategies on large-scale unlabeled text, i.e., masked language model and next sentence prediction. The pre-trained BERT model provides a powerful context-dependent sentence representation and can be used for various target tasks, i.e., intent classification and slot filling, through the fine-tuning procedure, similar to how it is used for other NLP tasks.

### 3.2 Joint Intent Classification and Slot Filling

BERT can be easily extended to a joint intent classification and slot filling model. Based on the hidden state of the first special token ([CLS]), denoted  $h_1$ , the intent is predicted as:

$$y^i = \text{softmax}(\mathbf{W}^i h_1 + \mathbf{b}^i), \quad (1)$$

For slot filling, we feed the final hidden states of other tokens  $h_2, \dots, h_T$  into a softmax layer to classify over the slot filling labels. To make this procedure compatible with the WordPiece tokenization, we feed each tokenized input word into a WordPiece tokenizer and use the hidden state corresponding to the first sub-token as input to the

Models	Snips			ATIS		
	Intent	Slot	Sent	Intent	Slot	Sent
RNN-LSTM (Hakkani-Tür et al., 2016)	96.9	87.3	73.2	92.6	94.3	80.7
Atten.-BiRNN (Liu and Lane, 2016)	96.7	87.8	74.1	91.1	94.2	78.9
Slot-Gated (Goo et al., 2018)	97.0	88.8	75.5	94.1	95.2	82.6
Joint BERT	<b>98.6</b>	<b>97.0</b>	<b>92.8</b>	97.5	<b>96.1</b>	88.2
Joint BERT + CRF	98.4	96.7	92.6	<b>97.9</b>	96.0	<b>88.6</b>

Table 2: 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 first group of models are cited from Goo et al. (2018).

softmax classifier.

$$y_n^s = \text{softmax}(\mathbf{W}^s \mathbf{h}_n + \mathbf{b}^s), n \in 1 \dots N \quad (2)$$

where  $\mathbf{h}_n$  is the hidden state corresponding to the first sub-token of word  $x_n$ .

To jointly model intent classification and slot filling, the objective is formulated as:

$$p(y^i, y^s | \mathbf{x}) = p(y^i | \mathbf{x}) \prod_{n=1}^N p(y_n^s | \mathbf{x}), \quad (3)$$

The learning objective is to maximize the conditional probability  $p(y^i, y^s | \mathbf{x})$ . The model is fine-tuned end-to-end via minimizing the cross-entropy loss.

### 3.3 Conditional Random Field

Slot label predictions are dependent on predictions for surrounding words. It has been shown that structured prediction models can improve the slot filling performance, such as conditional random fields (CRF). Zhou and Xu (2015) improves semantic role labeling by adding a CRF layer for a BiLSTM encoder. Here we investigate the efficacy of adding CRF for modeling slot label dependencies, on top of the joint BERT model.

## 4 Experiments and Analysis

We evaluate the proposed model on two public benchmark datasets, ATIS and Snips.

### 4.1 Data

The ATIS dataset (Tür et al., 2010) is widely used in NLU research, which includes audio recordings of people making flight reservations. We use the same data division as Goo et al. (2018) for both datasets. The training, development and test sets contain 4,478, 500 and 893 utterances, respectively. There are 120 slot labels and 21 intent types

for the training set. We also use Snips (Coucke et al., 2018), which is collected from the Snips personal voice assistant. The training, development and test sets contain 13,084, 700 and 700 utterances, respectively. There are 72 slot labels and 7 intent types for the training set.

### 4.2 Training Details

We use English uncased BERT-Base model<sup>1</sup>, which has 12 layers, 768 hidden states, and 12 heads. BERT is pre-trained on BooksCorpus (800M words) (Zhu et al., 2015) and English Wikipedia (2,500M words). For fine-tuning, all hyper-parameters are tuned on the development set. The maximum length is 50. The batch size is 128. Adam (Kingma and Ba, 2014) is used for optimization with an initial learning rate of 5e-5. The dropout probability is 0.1. The maximum number of epochs is selected from [1, 5, 10, 20, 30, 40].

### 4.3 Results

Model	Epochs	Intent	Slot
Joint BERT	30	98.6	97.0
No joint	30	98.0	95.8
Joint BERT	40	98.3	96.4
Joint BERT	20	99.0	96.0
Joint BERT	10	98.6	96.5
Joint BERT	5	98.0	95.1
Joint BERT	1	98.0	93.3

Table 3: Ablation Analysis for the Snips dataset.

Table 2 shows the model performance as slot filling F1, intent classification accuracy, and sentence-level semantic frame accuracy on the Snips and ATIS datasets.

<sup>1</sup><https://github.com/google-research/bert>

<b>Query</b>	need to see <b>mother joan of the angels</b> in one second							
Gold, predicted by joint BERT correctly								
<b>Intent</b>	SearchScreeningEvent							
<b>Slots</b>	O	O	O	B-movie-name	I-movie-name	I-movie-name	I-movie-name	B-timeRange
	I-timeRange	I-timeRange						
Predicted by Slot-Gated Model (Goo et al., 2018)								
<b>Intent</b>	BookRestaurant							
<b>Slots</b>	O	O	O	B-object-name	I-object-name	I-object-name	I-object-name	B-timeRange
	I-timeRange	I-timeRange						

Table 4: A case in the Snips dataset.

The first group of models are the baselines and it consists of the state-of-the-art joint intent classification and slot filling models: sequence-based joint model using BiLSTM (Hakkani-Tür et al., 2016), attention-based model (Liu and Lane, 2016), and slot-gated model (Goo et al., 2018).

The second group of models includes the proposed joint BERT models. As can be seen from Table 2, joint BERT models significantly outperform the baseline models on both datasets. On Snips, joint BERT achieves intent classification accuracy of 98.6% (from 97.0%), slot filling F1 of 97.0% (from 88.8%), and sentence-level semantic frame accuracy of 92.8% (from 75.5%). On ATIS, joint BERT achieves intent classification accuracy of 97.5% (from 94.1%), slot filling F1 of 96.1% (from 95.2%), and sentence-level semantic frame accuracy of 88.2% (from 82.6%). Joint BERT+CRF replaces the softmax classifier with CRF and it performs comparably to BERT, probably due to the self-attention mechanism in Transformer, which may have sufficiently modeled the label structures.

Compared to ATIS, Snips includes multiple domains and has a larger vocabulary. For the more complex Snips dataset, joint BERT achieves a large gain in the sentence-level semantic frame accuracy, from 75.5% to 92.8% (22.9% relative). This demonstrates the strong generalization capability of joint BERT model, considering that it is pre-trained on large-scale text from mismatched domains and genres (books and wikipedia). On ATIS, joint BERT also achieves significant improvement on the sentence-level semantic frame accuracy, from 82.6% to 88.2% (6.8% relative).

#### 4.4 Ablation Analysis and Case Study

We conduct ablation analysis on Snips, as shown in Table 3. Without joint learning, the accuracy of intent classification drops to 98.0% (from

98.6%), and the slot filling F1 drops to 95.8% (from 97.0%). We also compare the joint BERT model with different fine-tuning epochs. The joint BERT model fine-tuned with only 1 epoch already outperforms the first group of models in Table 2.

We further select a case from Snips, as in Table 4, showing how joint BERT outperforms the slot-gated model (Goo et al., 2018) by exploiting the language representation power of BERT to improve the generalization capability. In this case, “mother joan of the angels” is wrongly predicted by the slot-gated model as an object name and the intent is also wrong. However, joint BERT correctly predicts the slot labels and intent because “mother joan of the angels” is a movie entry in Wikipedia. The BERT model was pre-trained partly on Wikipedia and possibly learned this information for this rare phrase.

## 5 Conclusion

We propose a joint intent classification and slot filling model based on BERT, aiming at addressing the poor generalization capability of traditional NLU models. Experimental results show that our proposed joint BERT model outperforms BERT models modeling intent classification and slot filling separately, demonstrating the efficacy of exploiting the relationship between the two tasks. Our proposed joint BERT model achieves significant improvement on intent classification accuracy, slot filling F1, and sentence-level semantic frame accuracy on ATIS and Snips datasets over previous state-of-the-art models. Future work includes evaluations of the proposed approach on other large-scale and more complex NLU datasets, and exploring the efficacy of combining external knowledge with BERT.



## References

- Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2014. [Neural machine translation by jointly learning to align and translate](#). *CoRR*, abs/1409.0473.
- 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. 2018. [Snips voice platform: an embedded spoken language understanding system for private-by-design voice interfaces](#). *CoRR*, abs/1805.10190.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. [BERT: pre-training of deep bidirectional transformers for language understanding](#). *CoRR*, abs/1810.04805.
- 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 *NAACL-HLT, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 2 (Short Papers)*, pages 753–757.
- Daniel Guo, Gökhan Tür, Wen-tau Yih, and Geoffrey Zweig. 2014. [Joint semantic utterance classification and slot filling with recursive neural networks](#). In *2014 IEEE Spoken Language Technology Workshop, SLT 2014, South Lake Tahoe, NV, USA, December 7-10, 2014*, pages 554–559.
- Dilek Hakkani-Tür, Gökhan Tür, Asli Çelikyilmaz, Yun-Nung Chen, Jianfeng Gao, Li Deng, and Ye-Yi Wang. 2016. [Multi-domain joint semantic frame parsing using bi-directional RNN-LSTM](#). In *Interspeech 2016, San Francisco, CA, USA, September 8-12, 2016*, pages 715–719.
- Yoon Kim. 2014. [Convolutional neural networks for sentence classification](#). In *EMNLP 2014, October 25-29, 2014, Doha, Qatar; A meeting of SIGDAT, a Special Interest Group of the ACL*, pages 1746–1751. ACL.
- Diederik P. Kingma and Jimmy Ba. 2014. [Adam: A method for stochastic optimization](#). *CoRR*, abs/1412.6980.
- Gakuto Kurata, Bing Xiang, Bowen Zhou, and Mo Yu. 2016. [Leveraging sentence-level information with encoder LSTM for natural language understanding](#). *CoRR*, abs/1601.01530.
- Bing Liu and Ian Lane. 2016. [Attention-based recurrent neural network models for joint intent detection and slot filling](#). In *Interspeech 2016, San Francisco, CA, USA, September 8-12, 2016*, pages 685–689.
- Pengfei Liu, Xipeng Qiu, and Xuanjing Huang. 2017. [Adversarial multi-task learning for text classification](#). In *ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers*, pages 1–10. Association for Computational Linguistics.
- Baolin Peng, Kaisheng Yao, Li Jing, and Kam-Fai Wong. 2015. [Recurrent neural networks with external memory for spoken language understanding](#). In *NLPCC 2015, Nanchang, China, October 9-13, 2015, Proceedings*, pages 25–35.
- Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. [Deep contextualized word representations](#). In *NAACL-HLT 2018, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 1 (Long Papers)*, pages 2227–2237.
- Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. 2018. Improving language understanding with unsupervised learning. In *Technical report, OpenAI*.
- Suman V. Ravuri and Andreas Stolcke. 2015. [Recurrent neural network and LSTM models for lexical utterance classification](#). In *INTERSPEECH 2015, Dresden, Germany, September 6-10, 2015*, pages 135–139. ISCA.
- Gökhan Tür, Dilek Hakkani-Tür, and Larry P. Heck. 2010. [What is left to be understood in atis?](#) In *2010 IEEE Spoken Language Technology Workshop, SLT 2010, Berkeley, California, USA, December 12-15, 2010*, pages 19–24.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. [Attention is all you need](#). In *NIPS 2017, 4-9 December 2017, Long Beach, CA, USA*, pages 6000–6010.
- Ngoc Thang Vu. 2016. [Sequential convolutional neural networks for slot filling in spoken language understanding](#). In *Interspeech 2016, 17th Annual Conference of the International Speech Communication Association, San Francisco, CA, USA, September 8-12, 2016*, pages 3250–3254. ISCA.
- Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, Jeff Klingner, Apurva Shah, Melvin Johnson, Xiaobing Liu, Lukasz Kaiser, Stephan Gouws, Yoshikiyo Kato, Taku Kudo, Hideto Kazawa, Keith Stevens, George Kurian, Nishant Patil, Wei Wang, Cliff Young, Jason Smith, Jason Riesa, Alex Rudnick, Oriol Vinyals, Greg Corrado, Macduff Hughes, and Jeffrey Dean. 2016. [Google’s neural machine translation system: Bridging the gap between human and machine translation](#). *CoRR*, abs/1609.08144.
- 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, Olomouc, Czech Republic, December 8-12, 2013*, pages 78–83.

- Zichao Yang, Diyi Yang, Chris Dyer, Xiaodong He, Alexander J. Smola, and Eduard H. Hovy. 2016. [Hierarchical attention networks for document classification](#). In *NAACL HLT 2016, San Diego California, USA, June 12-17, 2016*, pages 1480–1489. The Association for Computational Linguistics.
- Kaisheng Yao, Baolin Peng, Yu Zhang, Dong Yu, Geoffrey Zweig, and Yangyang Shi. 2014. [Spoken language understanding using long short-term memory neural networks](#). In *2014 IEEE Spoken Language Technology Workshop, SLT 2014, South Lake Tahoe, NV, USA, December 7-10, 2014*, pages 189–194.
- Xiang Zhang, Junbo Jake Zhao, and Yann LeCun. 2015. [Character-level convolutional networks for text classification](#). In *NIPS 2015, December 7-12, 2015, Montreal, Quebec, Canada*, pages 649–657.
- Lin Zhao and Zhe Feng. 2018. [Improving slot filling in spoken language understanding with joint pointer and attention](#). In *ACL 2018, Melbourne, Australia, July 15-20, 2018, Volume 2: Short Papers*, pages 426–431.
- Zhiwei Zhao and Youzheng Wu. 2016. [Attention-based convolutional neural networks for sentence classification](#). In *Interspeech 2016, San Francisco, CA, USA, September 8-12, 2016*, pages 705–709. ISCA.
- Jie Zhou and Wei Xu. 2015. [End-to-end learning of semantic role labeling using recurrent neural networks](#). In *ACL 2015, July 26-31, 2015, Beijing, China, Volume 1: Long Papers*, pages 1127–1137.
- Yukun Zhu, Ryan Kiros, Richard S. Zemel, Ruslan Salakhutdinov, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. 2015. [Aligning books and movies: Towards story-like visual explanations by watching movies and reading books](#). In *2015 IEEE International Conference on Computer Vision, ICCV 2015, Santiago, Chile, December 7-13, 2015*, pages 19–27.