Out-of-Scope Domain and Intent Classification through Hierarchical Joint Modeling

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Abstract  User queries for a real-world dialog system may sometimes fall outside the scope of the system’s capabilities, but appropriate system responses will enable smooth processing throughout the human-computer interaction. This paper is concerned with the user’s intent, and focuses on out-of-scope intent classification in dialog systems. Although user intents are highly correlated with the application domain, few studies have exploited such correlations for intent classification. Rather than developing a two-stage approach that first classifies the domain and then the intent, we propose a hierarchical multi-task learning approach based on a joint model to classify domain and intent simultaneously. Novelties in the proposed approach include: (1) sharing supervised out-of-scope signals in joint modeling of domain and intent classification to replace a two-stage pipeline; and (2) introducing a hierarchical model that learns the intent and domain representations in the higher and lower layers respectively. Experiments show that the model outperforms existing methods in terms of accuracy, out-of-scope recall and $F_1$. Additionally, threshold-based post-processing further improves performance by balancing precision and recall in intent classification.

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1 Introduction

Intent classification [1] is one of the core components for NLU in dialog systems, where NLU needs to recognize the domain, intent and slots of a user query to make an appropriate response. Out-of-scope user queries are inevitable in a task-oriented dialog system, because it is difficult, if not impossible, to convey precisely and comprehensively to the system the range of capabilities of the system, especially in terms of the supported intents [2]. However, the problem of out-of-scope intent classification, which aims to find out the queries not belonging to any of the system-supported intents, is not so actively investigated due to lack of publicly available datasets. This problem is similar to out-of-distribution intent classification [3, 4], but poses new challenges since the out-of-scope queries are often similar with the in-scope queries, in terms of topics and/or styles [2]. Existing approaches to out-of-scope intent classification include: (1) two-step approaches which first perform binary classification of in-scope versus out-of-scope and in the former case further classify the specific in-scope intent [2, 4]; (2) classifier-based approaches that place out-of-scope query as an additional intent category [2, 5]; and further extend this with (3) a threshold for classification probabilities for each in-scope intent and optionally augmented with an out-of-scope intent [2, 6, 7].

As can be seen, out-of-scope intent classification has not yet been studied from the perspective of joint modeling or multi-task learning. Intent classification in dialog systems are highly dependent on supported domains, such as banking, restaurant, shopping etc., which means that domain information is useful for recognizing the intent of a user query. Although there has been studies on joint models for the tasks of intent classification and slot filling [8–16], multi-task joint modeling of domains and intents are rarely studied [12, 17, 18]. Furthermore, there still lacks deep understanding of the settings in which multi-task learning may bring significant benefits [19], in other words, how to effectively model the correlation between domain and intent classification in a multi-task learning framework. Remarkably, [19] introduced a hierarchical multi-task learning model for a set of carefully selected semantic tasks, aiming to supervise lower-level tasks (e.g., NER) at the bottom layers and more complex tasks (e.g., relation extraction) at the top layers of the model.

This paper presents a hierarchical joint model for out-of-scope domain and intent classification, where the two tasks of domain and intent classification share the same out-of-scope supervised signals through joint modeling, and a hierarchical structure is introduced in the network to learn the intent representation on top of the domain representation. The major benefits of joint modeling and hierarchical structure are information sharing and inheritance between domain and intent classification, which may present advantages over a two-stage pipeline approach of domain classification followed by intent classification. The motivation to introduce the hierarchical structure in the network are two-fold: (1) there are generally a larger number of intents than domains and consequently intent classification may need a more refined
(2) intent classification can generally benefit from additional domain-related information.

For example, in the user query of “My credit card was swallowed by ATM when I tried to withdraw some money. How can I get back my card?” — it is easy to determine the domain as banking based on the words like credit card or ATM, but requires a model of more refined understanding to determine that the intent is “report card swallowed” instead of “withdraw money”. Besides, knowing that the domain of the query is in banking gives additional information for intent classification. From the perspective of representation learning, the proposed joint model introduces a hierarchical bias whereby the higher layers represent intent information, while the lower layers represent domain information. Such an organization offer a better knowledge representation than a flat structure shared between domain and intent. The major contributions of this paper are:

(1) We propose a novel multi-task joint model for out-of-scope domain and intent classification, which outperforms state-of-the-art methods by a large margin;
(2) We introduce a hierarchical structure in the model to allow for hierarchical representation learning and information inheritance from domain to intent;
(3) We show that a threshold-based post-processing method improves the performance further by balancing precision and recall in out-of-scope intent classification.

2 Related Work

The problem of out-of-scope intent classification is not as actively studied due to lack of publicly available datasets [2][20][23], but is nonetheless very important especially in real-world dialog systems [24]. The out-of-scope problem encompasses cases where the intent of a user query is not supported by the dialog system but the query is similar in style and or topic to the in-scope queries, as is reflected by the term out-of-scope [2][5]. It also encompasses cases where the user query originates from another dataset and is substantially different from the in-distribution queries, which is literally an out-of-distribution problem [3][4]. For out-of-scope intent classification, [2] introduced a 150-intent dataset for evaluating out-of-scope prediction performance of intent classification systems, and presented BERT-based methods which are however poor at recognizing out-of-scope intents. In line with this formulation, [3] introduced a pre-trained language model named ToD-BERT which is learned from a bunch of task-oriented dialogue datasets and obtained better performance than BERT in terms of accuracy and out-of-scope recall on a downstream intent classification task. By contrast, [3] studied the out-of-distribution problem by forming out-of-distribution examples from another dataset and found that
classification with *softmax* distribution probabilities offer good performance on out-of-distribution detection. Similarly, [4] considered the intents excluded from the training set as out-of-distribution intents and adopted a novelty detection algorithm named *local outlier factor* to detect the unknown intents.

This paper presents a novel approach for out-of-scope intent classification based on joint modeling of domain and intent, together with hierarchical representation fine-tuning from the BERT model for the correlated tasks of domain and intent classification. Hierarchical multi-task learning has been introduced for semantic tasks such as named entity recognition, entity mention detection, coreference resolution and relation extraction [19]. Similarly, hierarchical modeling has also been applied to syntactic and semantic tasks in chunking, dependency parsing, semantic relatedness, and textual entailment [25]. To the best of our knowledge, the present work is the first to apply hierarchical joint modeling to out-of-scope domain and intent classification.

3 Hierarchical Joint Modeling

The proposed hierarchical joint model, named BERT-Joint, is illustrated in Figure 1, where a token sequence is fed into a BERT encoder to obtain a sequence of hidden states that are averaged by a pooling operation to obtain the BERT representation $\bar{h}$. The following modules are a domain encoder in red and an intent encoder in blue, as well as the subsequent *softmax* layers for domain and intent classification respectively. Particularly, the intent encoder is fed with the domain representation $d$ to model the hypothesis that intent classification needs additional domain information and requires more layers than domain classification to learn the intent representation $t$.

**BERT Representation.** For a given utterance, BERT [26] takes the word sequence $x = (x_1, x_2, ..., x_T)$ as input, and outputs a sequence of hidden states $h = (h_1, h_2, ..., h_T)$ after a few Transformer layers. Following the training schema in pre-trained BERT models, a special token [CLS] is added to the start of every sequence for aggregating the sequence representation and another special token [SEP] is appended to the end of every sequence for differentiating the sentences [26]. We used the average pooling vector $\bar{h} = \text{average-pooling}(h)$, as the BERT representation of an utterance, which gives slightly better performance than $h_1$ corresponding to [CLS].

**Domain Representation.** Given an utterance representation $\bar{h}$ from the BERT encoder, we first obtain a representation subspace $s_d$ from $\bar{h}$ using a non-linear transformation with the weight matrix $W_d$ and the additive bias $b_d$, and then apply residual connection [27] and layer normalization [28] to obtain the domain representation vector $d$, as illustrated in Equation (1) and (2), which are inspired from the Transformer model [29].
Fig. 1: The architecture of BERT-Joint model, where a pre-trained BERT model is adopted as the encoder, [CLS] and [SEP] are the two special tokens adding to the start and the end of each sequence respectively.

\[
s_d = \text{ReLU}(W_d h + b_d) \quad (1)
\]
\[
d = \text{LayerNorm}(s_d + h) \quad (2)
\]

**Intent Representation.** Similarly, we obtain a representation subspace \( s_t \), as in Equation (3), for intent transformed from the summation of the domain representation \( d \) and the BERT representation \( h \), where \( W_t \) is the weight matrix and \( b_t \) is the additive bias. We then apply residual connection and layer normalization to get the intent representation \( t \) in Equation (4).

\[
s_t = \text{ReLU}(W_t(d + h) + b_t) \quad (3)
\]
\[
t = \text{LayerNorm}(s_t + d) \quad (4)
\]

The intent representation \( t \) is built on top of the domain representation \( d \) to introduce a hierarchical structure in the network. Such hierarchical structure aims to capture the dependency between a domain and the corresponding intents, and model the hypothesis that additional domain information is useful for intent classification. Besides, we believe that intent classification needs a model with more layers than domain classification due to a larger number of
Joint Learning. We learn domain and intent classification jointly using two separate softmax layers on top of the corresponding representations, as illustrated in Equation (5-6), where \( p^d \) is the predicted domain distribution and \( p^l \) is the predicted intent distribution. We adopt the cross entropy loss for model training. \( L_d \) is the loss between the predicted domain distribution \( p^d \) and the true domain \( y^d \), where \( p_m^d \) means the predicted probability of being domain \( m \), and \( y_m^d \) is 1 if the true domain is \( m \) else 0. Similarly, \( L_t \) measures the loss between the predicted intent distributions \( p^l \) and the true intent \( y^l \), where \( p_n^l \) means the predicted probability of being intent \( n \). \( y_n^l \) is also a binary indicator which is 1 if the true intent is \( n \) and else 0. We optimize domain and intent classification jointly using a linear combination of their corresponding cross entropy loss, as shown in Equation (9), where the weight \( \lambda \) is also a learnable parameter, jointly learned with the other model parameters.

\[
p^d = \text{softmax}(W^d d + b^d) \tag{5}
\]
\[
p^l = \text{softmax}(W^l t + b^l) \tag{6}
\]
\[
L_d = - \sum_{m=1}^{M} y_m^d \log(p_m^d) \tag{7}
\]
\[
L_t = - \sum_{n=1}^{N} y_n^l \log(p_n^l) \tag{8}
\]
\[
L = \lambda L_d + (1 - \lambda)L_t \tag{9}
\]

Note that the number of domains \( M \) is much smaller than the number of intents \( N \) in real-world dialog systems, which means that it is easier to determine the domain of an utterance than the intent. As each utterance has both labels of domain and intent, the advantage of joint learning is that the discrimination capability learned by the domain classifier, particularly on out-of-scope user queries, are also shared with the intent classifier by feeding the domain representation to the subsequent intent representation layers.

Threshold-based Post-processing. Since out-of-scope examples are frequently misclassified as in-scope intents at low probabilities, we propose a threshold-based method to post-process the predicted probabilities, and consider an example as out-of-scope if the predicted probability is below the pre-specified threshold \( \tau \), (i.e., \( p^l < \tau \) for intent classification). It is interesting to observe that setting a threshold value generally improves both in-scope and out-of-scope accuracy. More importantly, the threshold-based post-processing method provides an effective way to balance precision and recall for out-of-scope intent classification.
4 Experiments

4.1 Experimental Setup

Dataset. We evaluate the proposed model using the OOS dataset \(^2\), which consists of 150 intents across 10 domains and a number of out-of-scope examples belonging to none of the domains or intents. The dataset is different from conventional intent datasets in the sense that it focuses on out-of-scope intent classification. The task is particularly challenging since the out-of-scope examples are similar in topics or styles with the in-scope examples but are not within any of the 150 in-scope intents. There are three variants of the OOS dataset, namely Small, Imbalanced and OOS+, where Small has the smallest number of total examples, and OOS+ has the largest number of out-of-scope examples. In contrast, Imbalanced has the imbalanced number of in-scope examples. The number of examples in each variant of the OOS dataset is shown in Table 1. Note that all the variants have the same test set which has 1000 out-of-scope examples and 150 * 30 in-scope examples.

|          | Full       | Small     | Imbalanced | OOS+     |
|----------|------------|-----------|------------|----------|
| Train    | Total Examples | 15100   | 7600       | 10625    | 15250    |
|          | #Out-of-scope Examples | 100   | 100        | 100      | 250      |
|          | #Examples per In-scope Intent | 100   | 50         | 25, 50, 75, 100 | 100      |
| Valid    | Total Examples | 3100   | 3100       | 3100     | 3100     |
|          | #Out-of-scope Examples | 100   | 100        | 100      | 100      |
|          | #Examples per In-scope Intent | 20   | 20         | 20       | 20       |
| Test     | Total Examples | 5500   | 5500       | 5500     | 5500     |
|          | #Out-of-scope Examples | 1000  | 1000       | 1000     | 1000     |
|          | #Examples per In-scope Intent | 30   | 30         | 30       | 30       |

Metrics. We adopt accuracy as the metric for evaluating the overall accuracy (all) on all the examples, and the in-scope accuracy (in) on the in-scope examples, for the OOS test set. For out-of-scope examples, we report the metrics of precision \((P)\), recall \((R)\) and \(F_1\).

Settings. We adopt the pre-trained BERT model of bert-base-uncased for an initial utterance representation. For fine-tuning, we used the AdamW \(^3\) optimizer and set the proportion of warm-up steps as 0.1, the learning rate as 4E-5. The maximum number of epochs is set as 10 on all the experiments except on OOS+, which has the largest number of training examples and obtains the best performance using 5 epochs. We adopted early stopping on condition that the intent classification accuracy does not improve for 3 epochs.

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\(^2\) https://github.com/clinc/oos-eval
We implemented the models using the PyTorch framework [31] and kept the random seed fixed on all the experiments for reproducible results.

4.2 Results and Discussion

Comparisons with Existing Methods. Table 2 presents the experimental results from [2] including the methods of FastText, SVM, CNN and BERT, and [5] covering GPT2, DialogGPT and ToD-BERT, as well our methods of BERT and BERT-Joint. It can be seen that the proposed BERT-Joint model obtains the best performance in terms of overall accuracy, and out-of-scope precision ($P$), recall ($R$) and $F_1$, and is further outperformed by applying a threshold-based post-processing method.

Table 2: Performance comparisons with existing methods for intent classification on the OOS test dataset (Full).

| Model            | Accuracy | $P$   | $R$   | $F_1$ |
|------------------|----------|-------|-------|-------|
|                  | all in   | out   | out   |       |
| Larson et al. [2]|          |       |       |       |
| FastText         | - 0.890  | - 0.097 | - 0.145 | - |
| SVM              | - 0.910  | - 0.189 | - 0.356 | - |
| CNN              | - 0.912  | - 0.189 | - 0.356 | - |
| BERT             | - 0.969  | - 0.403 | - 0.761 | - |
| Wu et al. [5]    |          |       |       |       |
| GPT2             | 0.830 0.941 | - 0.320 | - 0.370 | 0.537 |
| DialogGPT        | 0.839 0.955 | - 0.321 | - 0.463 | - |
| BERT             | 0.849 0.958 | - 0.356 | - 0.463 | - |
| ToD-BERT-mlm     | 0.859 0.961 | - 0.463 | - 0.649 | - |
| ToD-BERT-jnt     | 0.866 0.962 | - 0.436 | - 0.649 | - |
| This Work        |          |       |       |       |
| BERT             | 0.855 0.962 | 0.981 0.370 | 0.537 0.761 | 0.825 |
| BERT-Joint       | 0.876 0.964 | 0.984 0.484 | 0.649 0.761 | 0.825 |
| +Threshold       | 0.920 0.955 | 0.902 0.761 | 0.825 |

Error Analysis. We analyzed a few examples from the OOS test set, which are misclassified by either BERT or BERT-Joint, as shown in Table 3. Although Examples 1-4 are out-of-scope, users may naturally ask these questions as they do not precisely know about the system’s knowledge scope and capabilities. BERT-Joint makes correct predictions for Examples 3 and 4 but fails to reject Examples 1 and 2. Examples 5-7 are quite challenging, as they need a deeper semantic understanding of the sentences such as semantic inference (Example 6), discourse structure (Example 7). BERT-Joint classifies Examples 5 and 6 correctly on both domain and intent but not on Example 7, which actually consists of two sentences and the second sentence delivers the real intent. We notice that there are some annotation errors on intent in Examples 8-10. However, the predicted intents by both BERT and BERT-Joint are reasonable.
Table 3: Examples from the OOS test set for error analysis, where the labels in red are misclassified. Note that BERT only predicts the intent whereas BERT-Joint predicts both the domain and intent simultaneously.

(a) Testing Examples.

| ID | Example                                | Domain |
|----|----------------------------------------|--------|
| 1  | give me the weather forecast for today | oos    |
| 2  | how much data does my phone have left this month | oos |
| 3  | how many homeless people are there    | oos    |
| 4  | how do i learn more about linguistics | oos    |
| 5  | i would like to know my vacation days balance | work |
| 6  | does bank of america give credit cards to people like me | credit_cards |
| 7  | i’m trying to raise my credit score can you tell me what it is now | credit_cards |
| 8  | someone used my chase card without my authorization | credit_cards |
| 9  | can you call the help desk line for my credit card company | credit_cards |
| 10 | how can i request a new credit card   | credit_cards |

(b) Error Analysis.

| ID | Ground Truth | BERT | BERT-Joint |
|----|--------------|------|------------|
|    | Intent       | Domain | Intent     | Domain | Intent |
| 1  | oos          | weather | utility | weather |
| 2  | oos          | balance | utility | find_phone |
| 3  | oos          | traffic | oos      | oos    |
| 4  | oos          | translate | oos | oos |
| 5  | pto_balance  | balance | work    | pto_balance |
| 6  | new_card     | international_fees | credit_cards | new_card |
| 7  | credit_score | improve_credit_score | credit_cards | improve_credit_score |
| 8  | report_lost_card | report_fraud | banking | report_fraud |
| 9  | replacement_card_duration | make_call | credit_cards | make_call |
| 10 | replacement_card_duration | new_card | credit_cards | new_card |

Performance on Dataset Variants. We further verified the performance of BERT-Joint on the OOS variants, as shown in Table 4. We observe that

Table 4: Performance comparisons between BERT and BERT-Joint using different dataset variants of OOS.

|       | Model       | Accuracy | P  | R  | F₁ |
|-------|-------------|----------|----|----|----|
|       |             | all in   | out| out| out|
| Full  | BERT        | 0.855    | 0.962 | 0.981 | 0.370 | 0.537 |
|       | BERT-Joint  | 0.876    | 0.964 | 0.984 | 0.484 | 0.649 |
| Small | BERT        | 0.845    | 0.953 | 0.975 | 0.357 | 0.523 |
|       | BERT-Joint  | 0.865    | 0.954 | 0.981 | 0.464 | 0.630 |
| Imbalanced | BERT     | 0.855    | 0.952 | 0.981 | 0.423 | 0.591 |
|       | BERT-Joint  | 0.869    | 0.960 | 0.979 | 0.462 | 0.628 |
| OOS+  | BERT        | 0.882    | 0.959 | 0.983 | 0.536 | 0.694 |
|       | BERT-Joint  | 0.897    | 0.959 | 0.983 | 0.621 | 0.757 |
BERT-Joint consistently outperforms BERT on all the dataset variants in terms of overall accuracy, out-of-scope recall and $F_1$. Particularly, it improves the $F_1$ score of out-of-scope examples by an absolute increase of more than 10% on Full and Small, 3% on Imbalanced and 6% on OOS+.

**Effect of Hierarchical Structure.** The proposed approach of joint modeling of domain and intent is flexible to support various flat or hierarchical model structures. Here, flat means the domain representation and the intent representation are put side by side in the network, such as $F(h; h)$ which directly uses the same BERT output $h$ for domain and intent classification respectively, and $F(s_d; s_t)$ which adopts the subspace vectors $s_d$ and $s_t$ for the corresponding domain and intent classification. For hierarchical model structures, we consider both $H(s_t \rightarrow s_d)$ and $H(s_d \rightarrow s_t)$. The former structure means that we get the intent representation $s_t$ first and then feed it to the subsequent layers to get the domain representation $s_d$, while the latter first learns the domain representation $s_d$ which is then fed to the subsequent layers to get the intent representation $s_t$.

Table 5: Performance comparisons between BERT and BERT-Joint with different structures ($F$: Flat, $H$: Hierarchical).

| Model   | Structure | Accuracy | $P$    | $R$    | $F_1$   |
|---------|-----------|----------|--------|--------|---------|
|         |           |          | all in | out    | out     | out     | out     | out     |
| BERT    | -         | 0.8545   | 0.9622 | 0.9814 | 0.3700  | 0.5374  |
| Full    | F(h; h)   | 0.8689   | 0.9622 | 0.9825 | 0.4490  | 0.6163  |
|         | $F(s_d; s_t)$ | 0.8727   | 0.9604 | 0.9856 | 0.4780  | 0.6438  |
|         | $H(s_t \rightarrow s_d)$ | 0.8715   | 0.9611 | 0.9770 | 0.4680  | 0.6329  |
|         | $H(s_d \rightarrow s_t)$ | **0.8764** | **0.9636** | 0.9837 | **0.4840** | **0.6488** |
| Small   | -         | 0.8447   | 0.9531 | 0.9754 | 0.3570  | 0.5227  |
|         | F(h; h)   | 0.8529   | 0.9460 | 0.9731 | 0.4340  | 0.6003  |
|         | $F(s_d; s_t)$ | 0.8538   | 0.9500 | 0.9768 | 0.4210  | 0.5884  |
|         | $H(s_t \rightarrow s_d)$ | 0.8651   | **0.9573** | 0.9890 | 0.4500  | 0.6186  |
|         | $H(s_d \rightarrow s_t)$ | **0.8653** | 0.9544 | 0.9810 | **0.4640** | **0.6300** |
| Imbalanced | -       | 0.8555   | 0.9516 | 0.9814 | 0.4230  | 0.5912  |
|         | F(h; h)   | 0.8569   | 0.9544 | **0.9882** | 0.4180 | 0.5875  |
|         | $F(s_d; s_t)$ | 0.8673   | 0.9536 | 0.9796 | **0.4790** | **0.6434** |
|         | $H(s_t \rightarrow s_d)$ | 0.8689   | 0.9587 | 0.9873 | 0.4650  | 0.6322  |
|         | $H(s_d \rightarrow s_t)$ | **0.8693** | **0.9598** | 0.9788 | 0.4620  | 0.6277  |
| OOS+    | -         | 0.8829   | 0.9589 | 0.9835 | 0.5360  | 0.6939  |
|         | F(h; h)   | 0.9005   | 0.9600 | 0.9649 | 0.6330  | 0.7645  |
|         | $F(s_d; s_t)$ | **0.9053** | 0.9609 | **0.9762** | **0.6550** | **0.7840** |
|         | $H(s_t \rightarrow s_d)$ | 0.8973   | 0.9611 | 0.9744 | 0.6100  | 0.7503  |
|         | $H(s_d \rightarrow s_t)$ | **0.8985** | **0.9613** | **0.9762** | 0.6160  | 0.7554  |

Table 5 presents the performance comparisons between BERT and the variants of BERT-Joint covering the four different model structures. We have the following observations:
(1) All variants of BERT-Joint outperform the BERT model, which is not surprising since BERT-Joint takes advantage of additional domain information for intent classification;

(2) The flat structure of $F(s_d; s_t)$ consistently outperforms $F(\bar{h}; \bar{h})$ on all the datasets, which may indicate that $s_d$ and $s_t$ can capture effective features from the BERT representation $\bar{h}$ for the corresponding domain and intent classification;

(3) The hierarchical structures generally outperform flat structures in terms of accuracy (all) on all the datasets except OOS+ where the structure of $F(s_d; s_t)$ obtains the best accuracy (all), as well as out-of-scope recall and $F_1$;

(4) BERT-Joint is particularly effective in dealing with out-of-scope intent classification. For example, $H(s_d \rightarrow s_t)$ outperforms BERT in terms of $F_1$ by an absolute increase of more than 10% on both Full and Small. This may be attributed to the domain classification task which also needs to learn how to classify the out-of-domain examples. Such capability is inherited by the intent classifier through feeding the domain representation to the subsequent intent layers and thus the out-of-scope intent classification performance is improved further.

Threshold-based Post-processing. Figure 2 presents the performance comparisons on the validation dataset (V) and the testing dataset (T) of OOS with $\tau \in \{0.1, \ldots, 0.9\}$. It is clear to see that the threshold value $\tau$ affects all the metrics on both V and T, and thus the threshold-based post-processing method provides an effective way to balance precision and recall for out-of-scope intent classification.

In Figure 2 (a), with the increase of $\tau$, the accuracy (Acc.) improves first and then drops when $\tau > 0.4$, since the low-probability ($< \tau$) in-scope examples are now misclassified as out-of-scope. As illustrated in Figure 2 (a) and (b) for out-of-scope intent classification, $R$ keeps increasing at the expense of decreasing in $P$, whereas the highest $F_1$ is obtained at $\tau = 0.3$ on V and at $\tau = 0.6$ on T. Note that T has a much larger number of out-of-scope examples than V and thus requires a larger $\tau$ for better recall.

Representation Visualization. To deepen understanding of the out-of-scope classification problem, we further visualized the domain and intent representations from the test set of OOS using t-SNE [32], which visualizes high-dimensional vectors in a two or three-dimensional map. As illustrated in Figure 3 each color represents a domain (a) or an intent (b). The 10 in-scope domains are well separated in Figure 3 (a), so does the 150 in-scope intents in Figure 3 (b). Note that some points are overlapped in Figure 3 due to too many examples and domains/intents, best viewed when enlarged. The out-of-scope examples are mainly located in the same blue cluster in both (a) and (b), but quite a few out-of-scope examples are distributed across different domains or intents. This explains why it is difficult to classify the out-of-scope examples, and why the simple threshold-based method gives better performance on out-of-scope intent classification.
Fig. 2: Overall accuracy (Acc.) and out-of-scope intent classification performance ($P$, $R$, and $F_1$) on $V$ and $T$.

Fig. 3: Visualization of domain and intent representations using t-SNE, where each color indicates a domain (intent) and the out-of-scope examples are colored in blue, best viewed when enlarged.

5 Conclusion

This paper presents a novel hierarchical joint model based on BERT for out-of-scope domain and intent classification. The proposed model allows sharing of supervised signals between both classification tasks and introduces a structural bias to enable hierarchical representation learning from the pre-trained BERT representations. We empirically show that the model outperforms existing methods in terms of accuracy as well as out-of-scope recall and $F_1$ by a large margin on all the variants of the OOS dataset. These observations serve to illustrate the effectiveness of joint modeling and hierarchical structure of the model particularly in out-of-scope intent classification. Furthermore, we show that a threshold-based post-processing method improves the performance further and allows to effectively balance precision and recall in out-of-scope intent classification.
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