**AISFG: Abundant Information Slot Filling Generator**

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**Abstract**

As an essential component of task-oriented dialogue systems, slot filling requires enormous labeled training data in a certain domain. However, in most cases, there is little or no target domain training data available in the training stage. Thus, cross-domain slot filling has to cope with the data scarcity problem by zero/few-shot learning. Previous researches on zero/few-shot cross-domain slot filling focus on slot descriptions and examples while ignoring the slot type ambiguity and example ambiguity issues. To address these problems, we propose Abundant Information Slot Filling Generator (AISFG), a generative model with a novel query template that incorporates domain descriptions, slot descriptions, and examples with context. Experimental results show that our model outperforms state-of-the-art approaches in zero/few-shot slot filling task.1

1 Introduction

Slot filling is a critical part of downstream tasks in natural language understanding (NLU) such as dialogue systems. Recently, some supervised slot filling models have achieved state-of-the-art results within deep learning (Mesnil et al., 2013; Yao et al., 2013; Louvan and Magnini, 2018; Kim et al., 2019). Nonetheless, these methods have a strong dependency on the domain-specific labels, which is not capable of transferring to new domains that always contain little or no data. To alleviate the problem of resource gap between source and target domains, cross-domain zero-shot has become an important research direction in slot filling. However, most researches on slot filling utilize token-level classification frameworks, which means they either convert it to a BIO tag labeling task (Shah et al., 2019; Bapna et al., 2017; Du et al., 2021) or predict the start and end position as QA task in the sentence (Du et al., 2021; Yu et al., 2021a), to extract spans. Recently, prompt learning methods reformulate the downstream tasks to a similar form with the pre-training tasks, which can fully utilize the knowledge encoded in PLMs and improve the performance of the downstream tasks in the scenarios of data scarcity. Motivated by this, we consider making the slot filling task consistent with PLMs pre-training tasks.

In this paper, we propose a generative template-based zero-shot slot filling framework named Abundant Information Slot Filling Generator (AISFG), which utilizes pre-trained generative model as the backbone and generates responses in natural language style. Thus, the slot filling task is consistent with the pre-training task of the PLM. In particular, we notice that shared cross-domain slot types sometimes refer to totally different entities across different domains. For example, in the SNIPS dataset (Coucke et al., 2018), domains RateBook and SearchScreeningEvent share a common slot type object_type, but it refers to book type and movie schedule, respectively. We call this slot type ambiguity issue. Moreover, we argue that incorporating slot examples only is far from fully utilizing the example information. For instance, for sentence give 5 out of 6 stars to creatures of light and darkness, we give the slot description to find best rating with examples like 6 and 5, the model produces the wrong answer 5 but not 6. We conjecture that, the model just learn that predicting a number is satisfying from these two examples but does not understand what is the best rating means. We call this example ambiguity issue. Thus, we attach our attention to domain-specific descriptions and examples with context to alleviate the above two issues. Specifically, we design the query template by incorporating domain descriptions, slot descriptions and examples with context.

The contribution of this paper can be summarized in three aspects:

1. Contributed equally.
2. The source code is available at https://github.com/realyanyang/AISFG.
We propose a generative template-based zero-shot slot filling framework. To the best of our knowledge, we are the first to apply the generative framework to perform the zero-shot cross-domain slot filling task.

We focus on slot type ambiguity and example ambiguity, which is ignored by previous researches. We incorporate domain-specific descriptions and examples with context to the query template to handle these two issues.

The experimental results show that AISFG achieves better performance than the existing methods on the setting of zero/few-shot.

2 Methodology

2.1 Slot Filling as Generation

Given a sentence $x$ from domain $d \in D$, slot filling aims to predict a set of (slot type, span) pairs $(s, y)$, where $s \in S$ is a specific entity type from a fixed set of slot types, and $y = \{y_1, y_2, \ldots, y_i\}$ is a set of spans in sentence $x$. Most work on slot filling utilizes token-level classification frameworks, which means they either convert it to BIO tag labeling or predict the start and end position in the sentence, to extract spans.

In contrast to this convention, we frame slot filling as a conditional sequence generation task and solve it in a sequence-to-sequence manner. As shown in Figure 1, given a sentence $x$, domain $d$, slot type $s$ and target $y$, we construct natural language query $q = t_q(x, d, s)$ and response $r = t_r(y)$ based on the predefined template. The generative model takes $q$ as input and directly predicts $r$ in a generation manner.

Leveraging the rich knowledge in the pre-trained generative model is important for cross-domain slot filling, especially in zero/few-shot setting. Thus, we construct query and response as natural language sentences to naturally utilize them.

**Query Construction** To solve the slot type ambiguity and example ambiguity, we synthesize the query by incorporating domain descriptions, slot descriptions and examples with context. Specifically, query construction template is formulated as:

```
in domain 1, find the 2, like 3
in 4, in sentence: x.
```

where the blank 1, 2, 3, 4 are filled with domain description, slot description, example entity and context for example, respectively. To avoid data leakage, we construct examples and contexts manually to ensure the example entities are not appeared in the dataset. The predefined specific mappings between domain/slot and description/example/context are reported in Appendix A.1 and A.3. Moreover, a query example is illustrated in Figure 1.

**Response Construction** Ideally, the response should be as simple as possible to alleviate the generation difficulty. Besides, an explicit template is easily converted to the original format for compatibility. Thus, we construct response by concatenating target entities with commas:

```
y_1, y_2, \ldots, y_i.
```

where $y_i$ is the $i$-th entity span in sentence $x$. A response example is illustrated in Figure 1.

2.2 Train and Inference

The sequence-to-sequence model is instantiated as a pre-trained generative language model, such as BART (Lewis et al., 2020). In the training stage, for the input sentence $x$ with multiple slots, we build a training pair, which consists of a query and a response based on the templates above for each slot. We further fine-tune the parameters based on these training pairs to maximize the log likelihood for predicting gold responses just like in an ordinary generation task. In the inference stage, we
also build a query for each candidate slot, and the response \( \hat{r} \) is generated in an auto-regressive manner, which means selecting the token as the next token with the highest probability over the vocabulary set at each time step. Note that, although we do not explicitly restrict the response tokens should originate from the input sentence \( x \), AISFG can always do it (but there are exceptions, we show some cases in Section 3.4). Then, the response \( \hat{r} \) is split by commas to recover to the original format \( \hat{y} \) for evaluation.

3 Experiments

3.1 Setup

Dataset We evaluate our method on SNIPS (Coucke et al., 2018), a public spoken language understanding dataset which contains 7 domains and 39 slots. To simulate the cross-domain scenarios, we choose one domain as the target domain for test and the left six domains as the source domains for training following the setup of Liu et al. (2020).

However, domains in SNIPS are not completely independent with each other. To achieve a real cross-domain scenario, we use another commonly used dataset namely ATIS (Price, 1990) as the target domain to test our model which is trained on SNIPS.

Baselines We compare our method against a number of representative baselines as follows:

- **Concept Tagger (CT)** A slot-filling framework proposed by Gobbi et al. (2018), which utilizes original slot descriptions to generalize to unseen slot types.

- **Robust Zero-shot Tagger (RZT)** Besides leveraging slot descriptions like CT, RZT (Shah et al., 2019) further introduces examples to improve the robustness of zero-shot slot filling.

- **Coarse-to-fine Approach (Coach)** Coach (Liu et al., 2020) is a two-step coarse-to-fine model for slot-filling, which performs coarse-grained BIO labeling task in the first step and performs fine-grained slot type classification task in the second step. It also encodes slot descriptions to help recognize unseen slot types.

- **QA-driven slot filling (QASF)** QASF (Du et al., 2021) uses a linguistically motivated question generation strategy for converting slot descriptions and example values into natural questions and solves the slot filling by extracting spans from utterances with a span-based QA model.

3.2 Main Results

Cross-Domain Slot Filling The cross-domain slot filling results are reported in Table 1. In SNIPS dataset, AISFG outperforms the state-of-the-art models (QASF for zero-shot and Coach for few-shot) by 7.47% on the average F1 under zero-shot setting, 13.57% under 20-shot setting and 8.88% under 50-shot setting, which demonstrates the superiority of our method. We train AISFG on SNIPS dataset and test it on the ATIS dataset for simulating a real cross-domain scenario, results are reported in the bottom of Table 1. AISFG consistently outperforms the existing state-of-the-art approaches, especially in zero-shot setting, where AISFG achieves 32.31% F1 score improvement. The significant performance improvement proves that utilizing rich domain information to prompt knowledge in PLMs may be a shortcut for solving data scarcity issue.

Analysis on Seen versus Unseen Slots We divide the samples in each target domain into “seen” and “unseen” categories in the SNIPS dataset for further understanding the transferring ability of our model. Following Liu et al. (2020), an example is categorized as “unseen” as long as the slot does not

| Corpus       | Training Setting | Zero-shot | Few-shot on 20 samples | Few-shot on 50 samples |
|--------------|------------------|-----------|------------------------|------------------------|
| Domain↓Model→ | CT | RZT | Coach | QASF | AISFG | CT | RZT | Coach | AISFG | CT | RZT | Coach | AISFG |
| AddToPlaylist | 38.82 | 42.77 | 50.90 | 57.57 | 56.20 | 58.36 | 63.18 | 62.76 | 81.64 | 68.69 | 74.89 | 74.68 | 83.51 |
| BookRestaurant | 27.54 | 30.68 | 34.01 | 48.75 | 65.94 | 45.65 | 50.54 | 65.97 | 78.06 | 54.22 | 54.49 | 74.82 | 84.60 |
| GetWeather | 46.45 | 50.28 | 50.47 | 61.27 | 67.66 | 54.22 | 58.86 | 67.89 | 82.68 | 63.23 | 58.87 | 79.64 | 83.73 |
| PlayMusic | 32.86 | 33.12 | 32.01 | 38.54 | 50.12 | 46.35 | 47.20 | 54.04 | 77.59 | 54.32 | 59.20 | 66.38 | 78.79 |
| RateBook | 14.54 | 16.43 | 22.06 | 36.51 | 41.05 | 64.37 | 63.33 | 74.68 | 79.06 | 76.45 | 76.87 | 84.62 | 92.85 |
| SearchCreativeWork | 39.79 | 44.45 | 46.65 | 60.82 | 67.46 | 57.83 | 63.39 | 57.19 | 71.95 | 66.38 | 67.81 | 64.56 | 76.00 |
| SearchScreeningEvent | 13.83 | 12.25 | 25.63 | 27.72 | 35.05 | 48.59 | 49.18 | 67.38 | 73.91 | 70.67 | 74.58 | 83.85 | 91.29 |
| Average F1 | 50.15 | 32.85 | 37.39 | 47.31 | 54.78 | 53.62 | 56.53 | 64.27 | 77.84 | 68.45 | 66.67 | 75.51 | 84.39 |
| ATIS | 30.55 | 32.85 | 37.39 | 47.31 | 54.78 | 35.17 | 28.65 | 1.64 | - | 35.17 | 26.05 | 41.37 | 54.91 | 64.04 |

Table 1: F1-scores (%) on SNIPS and ATIS for different target domains under zero-shot and few-shot learning settings. Bold indicates the best results. '-' represents the result is missed in published papers.
Training Setting Zero-shot Few-shot on 50 samples
Domain↓ Model→ SD SD+DD SD+E SD+EC AISFG SD SD+DD SD+E SD+EC AISFG
AddToPlaylist 54.57 54.94 55.03 56.22 56.20 80.84 83.49 82.84 83.23 83.51
BookRestaurant 63.48 63.85 62.82 65.93 65.94 51.12 81.11 83.15 83.16 83.66 83.73
GetWeather 61.09 61.35 64.73 65.56 67.66 50.12 87.25 82.84 83.23 83.51 84.60
PlayMusic 44.41 44.99 46.51 47.48 50.12 78.62 78.50 78.06 78.68 78.79 82.84
RateBook 30.67 30.61 33.38 41.44 41.05 89.53 90.25 90.49 90.82 91.29
SearchCreativeWork 65.60 64.02 66.14 66.45 67.46 75.78 76.36 74.19 74.89 76.00
SearchScreeningEvent 30.33 30.18 32.81 34.61 35.05 89.53 90.25 90.49 90.82 91.29
Average F1 50.02 49.99 51.63 53.95 54.78 83.03 83.90 83.30 83.90 84.39
Table 2: F1-scores (%) on SNIPS for different target domains under zero-shot and few-shot learning settings. Bold indicates the best results.

Table 3: Averaged F1-scores (%) over all target domains on SNIPS dataset for “seen” and “unseen” slots. ‘-’ represents the result is missed in published papers. Table 3 shows the average F1 results on seen and unseen slots in target domains under zero-shot and 50-shot settings. From this table, AISFG achieves the best results in both seen and unseen slots, especially on unseen slots that differ in the same source domains, indicating that our model is capable of transferring knowledge from source to target domain. Besides, approaches leverage PLMs (i.e., QASF and AISFG) have significant advantages over others, which demonstrates utilizing knowledge encoded in PLMs can enhance the transferring ability.

3.3 Ablation Studies
To solve the slot type ambiguity issue and example ambiguity issue, we incorporate domain description and context for example to the query template, respectively. To understand the influence of these components in the query template, we perform ablation studies on the SNIPS dataset and report results in Table 2. In this table, SD, DD, E, EC refers to Slot Description, Domain Description, Example and Example with Context, respectively. For example, “SD+EC” represents the query template is built by domain description plus example with context.

The Effect of Domain Description Comparing SD versus SD+DD and SD+EC versus AISFG, we observe that incorporating domain descriptions can improve the performance under few-shot setting but not for zero-shot setting. We conjecture the reason is that, the domain description we used (shown in Table 4) is simply converted from the domain name and contains limited information, which is not enough to provide domain knowledge. However, when some target domain examples are given (i.e., few-shot), the meaning of domain descriptions can be enhanced by these training examples. Then, the domain description becomes a domain indicator and can be used to distinguish the slot types shared by different domains, resulting in improved performance.

The Effect of Context Example Comparing SD versus SD+EC and SD+DD versus AISFG, we observe that incorporating examples with contexts can further boost the performance in both zero-shot and few-shot settings, which demonstrates these examples with contexts are helpful for cross-domain slot filling. Moreover, SD+EC outperforms SD+E in both zero-shot and few-shot settings. Especially, for the zero-shot setting in domain RateBook, which contains plenty of ambiguity examples, SD+EC achieves 8.06% improvement over SD+E, which indicates contexts are useful to alleviate example ambiguity.

3.4 Error Analysis and Case Study
To better understand our proposed model, we analyze the error predictions in all cross-domain experiments on SNIPS dataset (Table 1) and categorize them into three types: boundary mistakes, vocabu-
4 Related Work

The main challenge of cross-domain slot filling is to handle domain-specific slot types which have few or no supervision signals during the training stage. To handle the unseen slots, previous methods introduce slot descriptions (Lee and Jha, 2019; Liu et al., 2020; Bapna et al., 2017) and slot examples (Guerini et al., 2018; Shah et al., 2019) to capture the semantic relationship between unseen slots and input sentences. Based on these researches, we incorporate more information, like domain description and example context, to boost the performance on unseen slots.

Typically, traditional methods formulate the slot filling task as a token-level classification task (Liu et al., 2020; Bapna et al., 2017; Shah et al., 2019; Wang et al., 2021). To leverage the knowledge encoded in pre-trained language models, RCSF (Yu et al., 2021b) utilizes BERT (Devlin et al., 2019) to predict the start/end position of the target slot entity. However, the downstream task (i.e., token/position prediction) is inconsistent with the pre-training task (i.e., Masked LM and NSP for BERT), which may limit the expressiveness of the PLM (Mehri and Eskenazi, 2021). To bridge the gap, we treat the slot filling as a generative task and utilize a PLM whose pre-training task is also a generative task.

5 Conclusion & Discussion

In this paper, we introduce a novel zero-shot cross-domain slot filling model named AISFG, which can adapt to unseen domains seamlessly with the help of domain and slot description and together with full context examples. Experiments show that our model significantly outperforms existing zero-shot cross-domain slot filling approaches. Moreover, we conduct error analysis and case study to better understand our proposed model and leave solving boundary mistakes and vocabulary mistakes as our future work.
Acknowledgments

This work was partially supported by National Natural Science Foundation under Grants U1936103 and 61921003.

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A Appendix

A.1 Domain Descriptions

| Domain               | Domain Description       |
|----------------------|--------------------------|
| AddToPlaylist        | add to playlist          |
| BookRestaurant       | book restaurant          |
| GetWeather           | get weather              |
| PlayMusic            | play music               |
| RateBook             | rate book                |
| SearchCreativeWork   | search creative work     |
| SearchScreeningEvent | search screening event   |

Table 4: Domain descriptions for different domains.

A.2 Implementation Details

For a fair comparison with QASF, which is based on BERT (Du et al., 2021), we instantiate the sequence-to-sequence model as BART-base, which contains a similar parameter size as BERT. Following Liu et al. (2020), we reserve 500 samples in target domain as the validation set and regard the rest as the test set. We use Adam optimizer (Kingma and Ba, 2015) with a learning rate 2e-5 to fine-tune all parameters. The batch size is set to 16 and the decoding beam search size for BART is set to 2. The early stop strategy with patience of 5 is used to save the best checkpoint based on validation set.

Similar to the baselines, we use F1 score as the evaluation metric. For a given query, the true positive is the prediction with exactly matched entity extraction boundaries.
### A.3 Illustration of Slot Description, Context and Example

| Domain               | Slot                  | Slot Description                                                                 | Context                                                                 | Example                                                                 |
|----------------------|-----------------------|---------------------------------------------------------------------------------|-------------------------------------------------------------------------|-------------------------------------------------------------------------|
| AddToPlaylist        | music_item            | music item                                                                      | funk outta here please add a piece to my playlist                      | piece                                                                   |
|                      | entity_name           | entity name                                                                     | i am going to add love letter to my list of parties                    | love letter                                                             |
|                      | playlist              | playlist                                                                        | add this song to my stay happy playlist                                | stay happy                                                              |
|                      | artist                | artist                                                                          | i am going to include the taylor swift track in my bass gaming playlist | taylor swift                                                            |
| BookRestaurant       | city                  | city                                                             | make a reservation at the best pub in shanghai                        | shanghai                                                                |
|                      | facility              | facility                                                                        | in washington reserve a tavern with baby chair                        | baby chair                                                              |
|                      | timeRange             | time range                                                                      | i need a reservation for the chinese food in cuba in 10 minutes        | in 10 minutes                                                           |
|                      | restaurant_name       | restaurant name                                                                 | i am going to talk to my friends                                      | kfc                                                                     |
|                      | cuisine               | cuisine                                                                         | i d like to reserve a table for one at a spanish restaurant in wesley | spanish                                                                 |
|                      | restaurant_type       | restaurant type                                                                 | i d like to reserve a buffet for my family                            | buffet                                                                  |
|                      | served_dish           | served dish                                                                     | find a restaurant serves hot-pot and make a reservation               | hot-pot                                                                 |
|                      | party_size_number     | number                                                                          | make a six-person reservation at an alpine wine bar                    | six-person                                                              |
|                      | poi                   | position                                                                        | i d want to reserve a restaurant near my hotel                        | near my hotel                                                           |
|                      | sort                  | type                                                                             | get a highly regarded sandwich shop in colombia                       | highly regarded                                                         |
|                      | spatial_relation      | spatial relation                                                                 | book a restaurant for 2 that is 10 minutes walk from here              | 10 minutes walk                                                         |
|                      | state_type            | state                                                                            | we d want to go to a brasserie in omaha that serves sicilian cuisine   | omaha                                                                   |
|                      | party_size_description| person                                                                          | book a table for sebastian perez and leclerc                          | sebastian perez and leclerc                                              |
| GetWeather           | city                  | city                                                             | in the temperature going down to 2 in shanghai                        | shanghai                                                                |
|                      | state_type            | state                                                                            | check the weather in omaha                                            | omaha                                                                   |
|                      | timeRange             | time range                                                                      | what is the forecast for haidian in next half an hour                 | in next half an hour                                                    |
|                      | country               | country                                                                         | will it rain in my present local street on 11/10/2023                 | present local street                                                    |
|                      | geographic_poi        | geographic position                                                             | in west lake park, how cold will it be tomorrow                        | west lake park                                                          |
|                      | condition_temperature | temperature                                                                     | will it get hotter in 2 hours                                         | hotter                                                                  |
|                      | condition_description | weather                                                                          | will it rain in 2 hours                                               | snow storm                                                              |
| PlayMusic            | genre                 | genre                                                                            | find me a lullaby in netease cloud music                              | lullaby                                                                 |
|                      | music_item            | music item                                                                      | funk outta here please add a piece to my playlist                      | netease cloud music                                                    |
|                      | year                  | year                                                                             | find me a lullaby in netease cloud music                              | 2021                                                                    |
|                      | playlist              | playlist                                                                        | add this song to my stay happy playlist                                | stay happy                                                              |
|                      | album                 | album                                                                           | play the album getting ready by eason chan                             | getting ready                                                           |
|                      | sort                  | sort                                                                            | play shall we talk by eason chan                                       | shall we talk                                                           |
|                      | artist                | artist                                                                          | i am going to include the taylor swift track in my bass gaming playlist | taylor swift                                                            |
| RateBook             | object_part_of_series_type | series                                                             | rate the sequel 0 point                                               | sequel                                                                  |
|                      | object_select         | this current                                                                     | the book deserves a 5 star                                            | the 5                                                                  |
|                      | rating_value          | rating value                                                                     | the book deserves a 5 star                                            | lessons from madame chic                                               |
|                      | object_name           | object name                                                                     | lessons from madame chic is a fine pick for anyone interested in fashion style | horror                                                                  |
|                      | object_type           | object type                                                                     | i am too timid to read horror literatures                              | star                                                                    |
|                      | rating_unit           | rating unit                                                                     | this book deserves a 5 star                                            | 10                                                                     |
|                      | best_rating           | best rating                                                                     | the highest rating for this book is 10                                 | paris baguette                                                          |
|                      |                      |                                                                                  |                                                                         | paris baguette                                                         |
| SearchCreativeWork   | object_name           | object name                                                                     | paris baguette is a bakery chain based in south korea owned by the spc group | paris baguette                                                         |
|                      | object_type           | object type                                                                     | paris baguette is a bakery chain based in south korea owned by the spc group | paris baguette                                                         |
| SearchScreeningEvent | timeRange             | time range                                                                      | the movie starts at half past eight pm                                 | half past eight pm                                                     |
|                      | movie_type            | movie type                                                                      | i want to see a comedy like green book                                 | comedy                                                                  |
|                      | object_type           | object type                                                                     | the castro theatre is the closest movie house showing green book       | movie house                                                            |
|                      | location_name         | location name                                                                   | the movie poster of green book                                         | movie poster                                                           |
|                      | spatial_relation      | spatial relation                                                                 | the castro theatre is the closest movie house showing green book       | the castro theatre                                                     |
|                      | movie_name            | movie name                                                                      | the castro theatre is the closest movie house showing green book       | green book                                                              |

Table 5: Illustration of slot description, context and example.