InstructionNER: A Multi-Task Instruction-Based Generative Framework for Few-shot NER

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Abstract

Recently, prompt-based methods have achieved significant performance in few-shot learning scenarios by bridging the gap between language model pre-training and fine-tuning for downstream tasks. However, existing prompt templates are mostly designed for sentence-level tasks and are inappropriate for sequence labeling objectives. To address the above issue, we propose a multi-task instruction-based generative framework, named InstructionNER, for low-resource named entity recognition. Specifically, we reformulate the NER task as a generation problem, which enriches source sentences with task-specific instructions and answer options, then inferences the entities and types in natural language. We further propose two auxiliary tasks, including entity extraction and entity typing, which enable the model to capture more boundary information of entities and deepen the understanding of entity type semantics, respectively. Experimental results show that our method consistently outperforms other baselines on five datasets in few-shot settings.

1 Introduction

Pre-trained language models (PLMs) have achieved remarkable performance in natural language understanding and natural language generation tasks (Devlin et al., 2019; Lewis et al., 2020; Raffel et al., 2020; Brown et al., 2020). By constructing self-supervised pre-training tasks, PLMs can learn plenty of syntactic, semantic, and even factual knowledge from a large amount of unlabeled corpus. As the increasing interests in exploring the knowledge learned by PLMs, prompt-based methods (Han et al., 2021) are proposed, which can reduce the gap between pre-training and fine-tuning process by reformulating the downstream tasks to pre-training-style tasks (Gao et al., 2021; Schick and Schütze, 2021; Sun et al., 2021). Benefiting from the smaller task gaps and the inspiring prompt templates, the latent knowledge in PLMs can be effectively mined when performing downstream tasks. Thus, the prompt-based PLMs achieve significant improvements in the low-resource scenarios.

The named entity recognition (NER) task, which requires the model to locate and classify named entities into predefined types, is generally formulated as a sequence labeling paradigm as shown in Figure 1a. NER serves as an important part for solving tasks such as information extraction (Ritter et al., 2012), question answering (Mollá et al., 2006) and other language understanding problems (Guo et al., 2009; Gao et al., 2018). Unfortunately, the annotation resources for token labeling are often scarce and expensive in the real world. Thus, few-shot NER becomes a challenging but practical research problem and receives a lot of attention. Although prompt-based learning methods have achieved excellent performance in data-scarce scenarios, most
of the existing templates-based methods are designed for sentence-level tasks and can be hardly fit for sequence labeling problems. Therefore, the traditional NER paradigm needs to be reformulated to a more suitable way for PLMs, so that the prompt-learning methods can be applied to NER tasks.

Recently, some works have started to reformulate NER tasks to sequence-to-sequence (seq2seq) tasks and integrate prompt-based methods. For instance, Cui et al. (2021) proposes a template-based generative method (Template) which converts the NER task to span classification task and classifies span candidates in the form of cloze task at the decoding stage based on BART (shown in Figure 1b). While this method outperforms traditional sequence labeling baselines in few-shot scenarios as the introduction of prompt, it needs to enumerate all span candidates, which is inelegant and time-consuming. BARTNER (Yan et al., 2021) proposes a pointer-based seq2seq architecture, which converts NER sub-tasks to a unified sequence generation task and predicts entities from the input sentences and the corresponding type indexes (shown in Figure 1c). LightNER (Chen et al., 2021) introduces prompt-tuning to the attention mechanism of BARTNER and achieves promising improvement in low-resource scenarios. Inspired by TemplatedNER which designs specific prompt templates as decoder’s input, and LightNER which introduces extra parameters as soft-prompts into the attention layer, we raise the question that, if we enrich the source sentence of generative PLMs with heuristic prompts, can this better stimulate the semantic knowledge learned in the pre-training stage and complete low-resource NER tasks?

To this end, we propose a multi-task instruction-based generative framework, named InstructionNER, for few-shot NER. Specifically, we reformulate the NER task as a natural language generation problem (shown in Figure 1d). For the source sentence, we design descriptive instructions to enable the model to understand different tasks (Wei et al., 2021), and employ an option mechanism including all candidate entity categories as constraints of output space. Then, for inference, T5 (Raffel et al., 2020) is required to generate the entity word and the corresponding type in the form of natural language, as we believe that unrestricted decoding would stimulate the latent knowledge of PLMs to complete entity extraction and recognition tasks to a larger extent. Furthermore, we introduce two auxiliary tasks, named entity extraction (EE) task and entity typing (ET) task. EE requires the model to only decode the entity names and learn to better capture the boundary information. ET aims at only predicting the entity types and enhancing PLMs’ understanding of type semantics. Our contributions can be summarized as follows: 1) To fully leverage the knowledge in language models, we reformulate the NER task as a novel seq2seq problem, which integrates descriptive task instructions and answer options into the source sentence, then requires the model to predict entity names and types in natural language. 2) Moreover, we propose two auxiliary tasks which can enhance the ability to capture entity boundaries and the understanding of type semantics. 3) Experiments on three NER benchmarks show the effectiveness of our proposed approach, especially in the data-scarce scenarios. In addition, we conduct a thorough analysis to show more characteristics of our approach.

2 Related Works

2.1 Named Entity Recognition

Currently, the most popular approach is to formulate NER as a sequence labeling task (Chiu and Nichols, 2016; Strubell et al., 2017; Liu et al., 2019, 2021), adding token-level classifiers or CRF (Ma and Hovy, 2016) on top of sentence encoders. This formulation is naturally suitable for flat NER, but can hardly fit for other subtasks (Ratinov and Roth, 2009; Metke-Jimenez and Karimi, 2016; Straková et al., 2019; Dai et al., 2020). Inspired by the recent success of pre-trained seq2seq models, BARTNER (Yan et al., 2021) reformulated all the three kinds of NER subtasks as a generation problem, and purposed a pointer-based framework to inference entities as well as their type index using BART (Lewis et al., 2020). Motivated by this new formulation, we treat NER as a natural language generation task, where the model is required to generate entity names and corresponding types in the form of natural language. Moreover, we employ T5 (Raffel et al., 2020) instead of BART as our base model, as the pre-training task of T5 is to predict the sequence of corrupted tokens, which is more suitable for our formulation.

2.2 Prompt-based Methods

Prompt-based learning With the emergence of large pre-trained models like GPT3 (Brown et al.,
more and more researchers have begun to pay attention to a new fine-tuning paradigm, which is prompt-based learning. This new paradigm can make the best use of knowledge learned in the pre-training stage and thus achieve better performances in few-shot scenarios (Han et al., 2021). Another line of work that tries to stimulate the potential of pre-trained models is instruction-based methods (Schick and Schütze, 2021; Mishra et al., 2021). Wei et al. (2021) proposed to fine-tune language models on a collection of task descriptions and answer options, for improving their abilities to respond to natural language instructions and better generalize to unseen tasks. Inspired by their work, we introduce designed instruction templates to describe each task and answer options, including candidate entity categories of the current dataset.

**Prompt-based Few-shot NER** To make full use of language models in low-resource NER, Cui et al. (2021) proposed template-based BART, which treated original sentences as the source sequence, and statement templates filled by candidate spans as the target sequence. By introducing templates, this method outperforms traditional sequence labeling in few-shot scenarios, but it would be time-consuming to enumerate and classify all candidate spans. Following BARTNER, LightNER (Chen et al., 2021) incorporated continuous prompts into the self-attention matrix and constructed a semantic-aware answer space to replace label-specific layers. Different from their method, we inject task instructions and answer options into the source sentence, to stimulate more natural language knowledge from pre-trained models in few-shot settings.

### 3 Methodology

In this section, we introduce the overall framework of our proposed InstructionNER. We first briefly describe the problem definition of NER, then we discuss how we convert NER to the seq2seq form so that it can be solved through T5. Next, we propose two auxiliary tasks, named entity extraction and entity typing, which help the model to better identify the entities for both the boundary and the type. Finally, we introduce the parsing algorithm that converts the output of T5 (i.e., the word sequence) to the regular NER output (i.e., the triplet forms).

**Problem Definition** The task of NER aims to recognize all entity occurrences \( y \) in a given sentence \( x = \{w_1, w_2, \ldots, w_n\} \), where \( n \) represents the length of \( x \). The \( i \)-th entity occurrence \( y_i \in y \) can be formulated as a triplet: \( y_i = (l, r, t) \), where \( l \) and \( r \) indicate the left and right boundary indexes of the entity in the sentence \( x \), respectively. And \( t \in T \) indicates the entity type, where \( T \) is the full set of entity types.

For simplicity, we use \( x_{l:r} \) to represent the span of \( x \) from the left boundary \( l \) to the right boundary \( r \) (inclusive), i.e., \( x_{l:r} = \{w_l, \ldots, w_r\} \). Base on this, the entity occurrence \( y_i \) = \((l, r, t)\) indicates that the span \( x_{l:r} \) of sentence \( x \) is recognized as an entity of type \( t \).

**Solving NER through T5** To better transfer and utilize the knowledge learned in pre-trained language models, we reformulate the NER task to the seq2seq form and solve it through fine-tuning T5 (Raffel et al., 2020), as shown in Figure 2.

Specifically, for the main task (illustrated in the orange block in Figure 2), each input consists of the following three fields:

- **Sentence** - the source sentence \( x \).

- **Instruction** - the instruction tells the model which tasks the current sample belongs to. The model is trained to generate expected outputs that are consistent with the instruction. For the main NER task, the instruction is please extract entities and their types from the input sentence, all entity types are in options.

- **Options** - all entity types \( T \), split by comma. This field acts as both a hint and a constraint to remind the model which entity types need to be recognized.

To stimulate the potential of the pre-trained model, we organize the output into a natural language form that naturally responds to the command of the input. Specifically, for the entity occurrence \((l, r, t)\), we convert it to the natural language form using the template: \( x_{l:r} \) is a/an \( t \), and concatenate all converted entity occurrences together to make up an output sentence (using the comma as the separator and ending with the dot).

Specially, we have two strategies for filling the entity type \( t \) in the template. One is naturally using the token or phrase of \( t \) (e.g., using two tokens “restaurant name” to represent the entity type
“restaurant_name”). Another is using synthetic tokens that represent \( t \) (e.g., using a special token “\(<\text{restaurant}_\text{name}\>\)” to represent the entity type “restaurant_name”). The newly added special tokens would be appended to the token vocabulary of PLMs, and their embeddings are randomly initialized during the fine-tuning phase. We compare both strategies in our analysis experiments and get interesting results.

**Auxiliary Tasks** To boost the performance in a more fine-grained level, we further design two auxiliary tasks, namely entity extraction and entity typing, which are exactly two fine-grained subtasks that compose the full NER task. We train the model jointly with these auxiliary tasks.

For the entity extraction task, the model is trained to extract the entity spans from the given sentence, but is not required to type them. We replace the instruction field with \textit{please extract entity words from the input sentence} to identify this task, and remove the options field. Besides, the output should only contain the extracted spans, with “is a/an \( t \)” deleted. The entity extraction task is a simplification of the main task. Guided by the instruction, the model only needs to extract the entities from sentences without focusing on the category information of the extracted entities, which helps a lot for improving the span F1 of entity extraction. The improvement of span F1 means that the ability to correctly extract entities from sentences is strengthened, and thus the accuracy on the NER main task is improved as well.

For the entity typing task, the model is trained to type the given entity occurrences in the sentence. Specifically, we replace the instruction field of the input sample with \textit{please typing these entity words according to the sentence: \(<\text{the given entity occurrences}\>\)}, with other fields and the output same as the main task. In the training stage, as occurrences of entities in the sentence are given, we expect the model to focus more on capturing the category semantic information of entity occurrences. This encourages the model to generate more accurate category labels while maintaining the accuracy of entity occurrences generation in the main NER task, thus improving the performance of NER.

**Evaluation** The evaluation procedure of InstructionNER is shown in the half bottom of Figure 2. Given the sentence \( x \), we first wrap it with the same template as we train the main NER task. Then we feed the input to the T5 model and obtain the generated output\(^1\).

Once the output is obtained, we run the parsing algorithm to convert it to regular NER output as follows: 1) We split the output sentence by comma, and obtain multiple sub-sentences. 2) For each sub-sentence, we try to find the “is a/an” span. 3) If such a span is found, we intercept the prefix and suffix of the sub-sentence, and match them to the source sentence \( x \) to get predicted boundary indexes \( \hat{l}, \hat{r} \) and the set of entity types \( \mathcal{T} \) to get predicted type \( \hat{t} \), respectively. Then, we obtain a complete predicted triplet \((\hat{l}, \hat{r}, \hat{t})\). Once any step fails to match, we ignore this sub-sentence. After that, we compare predictions to the ground truth.

\(^1\)Since T5 is a generative model, the beam search is used when evaluating.
and use the F1 score as our main metrics.

4 Experiments

In this section, we conduct exhaustive few-shot experiments to evaluate the proposed InstructionNER framework and verify the effectiveness of the proposed multi-task strategy by comparing the performance of different implementations.

4.1 Setup

Datasets  Following Chen et al. (2021); Cui et al. (2021), we use CoNLL-2003 as the rich-resource domain dataset, and following the settings in (Ziyadi et al., 2020; Huang et al., 2020), we use MIT Movie Review, MIT Restaurant Review (Liu et al., 2019) and Airline Travel Information Systems (ATIS) (Hakkani-Tür et al., 2016) dataset as low-resource datasets.

Baselines and Our Implementations  In our experiments, we compare our methods with three types of NER methods and different variants of InstructionNER. 1) Sequence labeling Methods: There are two methods, including LC-BERT and LC-BART, which apply the traditional sequence labeling method for named entity recognition with BERT and BART respectively. 2) Template-based Methods: A method proposed by (Cui et al., 2021), which uses a BART-based seq2seq structure model to type all the enumerated spans by completing the human-designed template in line with the cloze task. We call this method Template for simplification. 3) Generative seq2seq Methods: BART-NER is a pointer-based seq2seq framework proposed by (Yan et al., 2021), which convert the NER task to a unified sequence generation with a pointer mechanism. LightNER has a similar architecture with BART, but they introduce a prompt-guided attention mechanism, which is the only tuned module in the training process. 4) Our Implementations InstructionNER is trained without auxiliary task and InstructionNER+ET/EE/ET, EE is trained with the ET/EE/both auxiliary task(s), respectively.

Settings  In NER tasks, different from the classification tasks at the sentence level, each instance often has multiple entities. If we sample k sentences for each type of entity from the training set directly, the number of various entities in the sampled set will exceed k. In this paper, a greedy sampling strategy is utilized to guarantee the number of instances for each entity type is equal to k in the few-shot training set following Yang and Katiyar (2020). If the number of occurrences of some entities is less than k in the training set, we will sample all these entities into the few-shot training set to keep in line with LightNER and Template. As the randomness of few-shot sampling, we repeat the sampling three times for each setting and report the average results and corresponding standard deviation. For fair comparisons with LightNER, Template, and BART-NER which employ BART-large as the base model, we also use the large version of T5 (T5-large) as the backbone model\(^2\). To keep the stability of the few-shot setting, we set the batch size to 2/4/8 for the 10/20/50 shot settings, respectively. In addition, we set the batch size to 16 for experiments with abundant samples. The learning rate of the Adam optimizer is set to 2e-5/5e-5, and the decoding beam search size is set to 2 to ensure more stable results and faster decoding speeds. More implement details are in appendix A.

Metrics  Similar to the baselines, we use F1 score as the evaluation metric for NER task. Besides, span F1 score is used to evaluate the entity extraction performance. The difference between F1 and span F1 is that, the true positive for F1 is the predictions with exactly matched entity extraction boundaries and correct entity type, while the true positive for span F1 only requires exactly matched entity extraction boundaries but ignores the entity type.

4.2 Main Results

Table 1 shows the results of the proposed methods with various implementations and the competitive baselines. From the table, we have the following observations: 1) Under the setting of 10/20/50-shot, which are common in few-shot settings, our methods consistently outperform the compared baselines. Especially under the 10-shot setting, compared to LightNER, our best implementation achieves 24.4%, 10.9%, and 13.1% F1 improvement on MIT Movie dataset, MIT Restaurant dataset, and ATIS dataset, respectively. 2) In our variants, the best implementation on MIT Movie dataset under the 10-shot setting (i.e., InstructionNER+EE) even outperforms the Template under 200-shot setting, which demonstrates the superiority of our model. 3) When under the extreme data-scarce scenario (i.e., the 10-shot set-

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\(^2\)If it is not specifically specified, the models used in our paper are all T5-Large (https://huggingface.co/t5-large).
Table 1: F1 score(%) on three datasets under different shot settings. The value in brackets represents the standard deviation. **Bold** numbers indicate the best performance across baselines and our implementations, and **underline** indicates the best performance in baselines or our implementations. "∗" indicates our reproduction results.

| Methods                  | MIT Movie | MIT Restaurant | ATIS |
|--------------------------|-----------|----------------|------|
|                           | 10        | 20             | 50   | 10 | 20 | 50 |
| **Baselines**             |           |                |      |    |    |    |
| LC-BERT                  | 25.2      | 42.2           | 49.6 | 44.1 | 76.7 | 90.7 |
| LC-BART                  | 10.2      | 27.5           | 44.2 | 42.0 | 72.7 | 87.5 |
| Template                 | 37.3      | 48.5           | 52.2 | 71.7 | 79.4 | 92.6 |
| BARTNER*                 | 41.1      | 54.0           | 67.7 | 58.0 | 57.8 | 86.1 |
| LightNER                 | 41.7      | 57.5           | 73.1 | 76.7 | 83.3 | 92.8 |
| **Our implementations**  |           |                |      |    |    |    |
| InstructionNER           | 64.4 (±2.1) | 70.0 (±0.3) | 74.1 (±1.2) | 65.5 (±1.4) | 71.2 (±1.1) | 90.7 (±0.3) |
| InstructionNER+ET        | 66.4 (±2.5) | 70.8 (±0.2) | 75.6 (±0.8) | 67.2 (±0.8) | 71.8 (±1.0) | 90.8 (±0.4) |
| InstructionNER+EE        | 66.5 (±3.0) | 70.1 (±1.9) | 74.7 (±0.3) | 68.9 (±0.9) | 71.1 (±0.9) | 90.6 (±0.4) |

4.3 Ablation Analysis

Experimental results in Table 1 show that our proposed InstructionNER has an outstanding ability for few-shot learning. To explore the influence of instruction-tuning and two auxiliary tasks on model performance, in this section, we do ablation analyses to compare and analyze our implementations in the bottom half of Table 1. We also conduct extra experiments to support our analysis.

**Instruction** To demonstrate the effect of the instruction and the options, we conduct experiments that remove the instruction field and the options field when constructing the input (i.e., only input the raw sentence), but keep the output form unchanged (still the “*a,l,r,*” template for each entity occurrence (l, r, t)). Such a pattern is consistent with the pre-training phase of T5, where all tasks are converted to the seq2seq form. We call this baseline T5-natural.

In Figure 3, we show the performance comparison between T5-natural and InstructionNER on. As shown in Table 1, incorporating ET and EE auxiliary tasks can further boost the performance of InstructionNER under the low-resource NER settings. Specifically, under the typical low-resource settings of 10/20/50-shot, ET achieves 0.4/1.5/1.1 improvement on F1 score(%) and EE achieves 1.2/1.0/0.6 improvement on F1 score(%) on average in MIT Movie and MIT Restaurant dataset. To further explore the effec-
we notice that the performance is dropped when we
when entity extraction is unchanged. 2) For In-
t5-v1_1-large
for more details.
See
https://huggingface.co/google/
trained on C4 only without mixing in the downstream
tasks. There are some un-
large is not only trained on unsupervised data (C4)
but also on supervised tasks. There are some un-
structionNER on T5-v1.1
proposed methods). The experimental results are
shown in 2, and we would like to analyze the results
from the following three perspectives:
chosen in 2, and we would like to analyze the results
from the following three perspectives:

| Methods          | CoNLL03          | Ontonotes5.0     | MIT Movie        |
|------------------|------------------|------------------|-----------------|
|                  | 10   | 20   | 50   | 10   | 20   | 50   | 10   | 20   | 50   |
| Template         | 44.8 ±(3.9) | 64.3 ±(5.3) | 72.8 ±(3.2) | 24.1 ±(4.1) | 36.5 ±(1.1) | 43.9 ±(0.8) | 38.7 ±(3.2) | 52.7 ±(1.4) | 61.1 ±(2.8) |
| BARTNER          | 45.7 ±(4.9) | 62.4 ±(5.4) | 72.7 ±(1.7) | 20.9 ±(3.2) | 33.2 ±(1.8) | 44.6 ±(2.2) | 41.1 ±(1.5) | 54.0 ±(0.3) | 67.7 ±(1.3) |
| BART_Instruction | 15.4 ±(2.6) | 31.6 ±(2.9) | 39.0 ±(1.2) | 12.4 ±(2.0) | 21.7 ±(1.6) | 34.4 ±(1.8) | 21.3 ±(4.4) | 38.7 ±(2.6) | 51.3 ±(4.0) |
| InstructionNER_base | 59.8 ±(2.2) | 60.3 ±(0.2) | 75.8 ±(2.3) | 30.5 ±(2.0) | 39.6 ±(2.3) | 48.5 ±(1.5) | 58.9 ±(4.2) | 66.2 ±(0.7) | 72.8 ±(1.8) |
| InstructionNER_v1.1 | 60.1 ±(0.3) | 763 ±(1.5) | 77.6 ±(1.2) | 34.7 ±(2.0) | 42.0 ±(0.6) | 51.4 ±(0.9) | 66.4 ±(2.3) | 69.2 ±(1.4) | 76.1 ±(0.7) |
| InstructionNER   | 61.3 ±(2.0) | 67.2 ±(1.9) | 76.3 ±(1.0) | 32.5 ±(2.8) | 41.4 ±(2.0) | 50.2 ±(1.5) | 64.4 ±(2.1) | 76.0 ±(0.3) | 74.1 ±(1.2) |

Table 2: F1 score(%) on CoNLL03, Ontonotes5.0, MIT Movie under 10/20/50-shot settings. The value in brackets represents the standard deviation.

tiveness of the two auxiliary tasks, we evaluate the
span F1 score on MIT Restaurant and MIT Movie
datasets. As shown in Figure 4, we have the follow-
ing observations: 1) For InstructionNER_ET, the
improvement on F1 score is more evident than the
improvement on span F1 score. This phenomenon is consistent with the goal of the ET task that im-
proves the performance of entity type classification
when entity extraction is unchanged. 2) For In-
structionNER-EE, the improvement of F1 score and
span F1 score is approximately the same propor-
tion, which indicates that incorporating EE task
can extract more accurate entity boundaries and
results in the improvement of NER task. Besides,
we notice that the performance is dropped when we
combine the ET and EE tasks. We conjecture the
reason is that the data size ratio between the main
and the auxiliary tasks is reduced to 1:2 when
introducing ET and EE simultaneously, which may
bring some noise to the main task.

5 Analysis

5.1 Comparison of Different PLMs

In this section, we conduct experiments on CoNLL03, Ontonotes5.0 and MIT-Movie, to make a detailed comparison between Template, BART-
NER, BART_Instruction (i.e., InstructionNER on BART), InstructionNER_base (i.e., Instruction-
NER on T5-base), InstructionNER_v1.1 (i.e., In-
structionNER on T5-v1.1), InstructionNER and the proposed methods). The experimental results are
shown in 2, and we would like to analyze the results
from the following three perspectives:

Comparison Fairness Considering that T5-
large is not only trained on unsupervised data (C4)
but also on supervised tasks. There are some un-
fair comparisons. We replace T5 with T5 v1.1 and
conduct experiments under InstructionNER frame-
work. We find that the performance of the two
implementations is close, which means that our im-
provements do not rely on the T5 version trained
on supervised tasks.

BART vs. T5 When observing the results of
BART_Instruction, we find that if BART is used as
the backbone, the model performs very badly. We
think that the difference in performance is due to
the pre-training task. BART needs to fully recon-
structure the original input, while T5 only needs to
predict the corrupted tokens, whose formulation is
closer to our proposed Instruction-based NER task.
Therefore, we employ T5 as the backbone in our
experiments.

Model Scale When observing the results of
InstructionNER_base, we can see that although our
proposed model uses T5 base as the backbone with
fewer parameters, it also outperforms Template,
which is based on BART-large. This proves that the
Instruction-based framework is very effective
for mining knowledge in text-to-text PLMs.

5.2 Transfer Analysis

In this section, we mainly focus on analyzing the
performance of the proposed model in the low-
resource cross-domain scenarios. Following Chen
et al. (2021) and Cui et al. (2021), we transfer the
model trained on CoNLL03 (i.e., source domain)
to MIT Restaurant (i.e., target domain) and ran-
donomly sample 10/20/50 instances per entity type
as the continual training data. Three prototype-
based methods, namely Neigh.Tag.(Wiseman and
Stratos, 2019), Example.(Ziyadi et al., 2020), and
MP-NSP(Huang et al., 2020), respectively, are fur-
ther introduced for comparison in the transfer sce-
narios.

As shown in Table 3, the proposed Instruction-
NER outperforms the baselines in all three settings,
which shows that our proposed model has good
performance in the cross-domain few-shot NER
task. Comparing the performance improvement
Table 3: F1 score(%) on MIT Restaurant dataset under transfer setting. The value in brackets represents the improvement compared to the in-domain results (i.e., results in Table 1). **Bold** numbers indicate the best performance. “∗” indicates our reproduction results.

| Methods   | MIT Restaurant |
|-----------|----------------|
| Baselines |                |
| Neigh.Tag. | 4.1 3.6 4.0     |
| Example.  | 25.2 26.1 26.8  |
| MP-NSP    | 46.1 48.2 49.6  |
| LC-BERT   | 27.2(4.5) 40.9(1.5) 56.3(+3.6) |
| LC-BART   | 8.8(+2.5) 11.1(+2.6) 42.7(-8.6) |
| Template  | 53.1(+7.1) 60.3(+3.2) 64.1(+5.4) |
| BARTNER*  | 55.0(+11.0) 64.0(+8.0) 71.5(+7.5) |
| LightNER  | 58.1(+9.6) 67.4(+9.4) 69.5(+7.5) |
| **Our implementations** |                |
| T5-natural| 55.8(+2.6) 63.6(+1.2) 68.6(-0.5) |
| InstructionNER | **63.7(+5.0)** 68.2(+2.7) 71.9(+0.7)** |

of all methods after transferring, we find that the performance of LightNER has the most improvement. LightNER introduces the prompt-guided attention mechanism and this mechanism requires the model to update only a few parameters at every fine-tuning step, which prevents the model from overfitting in the source domain and strengthens the effect of cross-domain transfer. In addition, it is noticed that, in cross-domain transfer experiments, the performance of T5-natural is the worst and sometimes even has a negative impact. One possible reason is that T5-natural is an unrestricted seq2seq NER architecture, when the input text in the source domain differentiates a lot from the text in the target domain, the knowledge learned in the source domain is limited and even treated as noise, which has a negative impact. However, InstructionNER prompts the input and output of the model via instruction and options. Thus, when the model is transferred from the source domain to the target domain, the variance of options can help the model adapt to the new domain and improve the transfer performance of the generative NER framework.

5.3 Label Semantic Analysis

As mentioned in Section 3, there are two strategies to fill the entity types in the template. One is using the natural language form, while the other regards type words as synthesized tokens and adding them to the vocabulary. Intuitively, InstructionNER can leverage the semantic information in label words to enhance the model in low-resource scenarios. In previous experiments, we use the setting of type words in the natural language form except for the experiments on ATIS\(^5\). In this section, we explore the influence of the two strategies on the performance of InstructionNER. We design multiple experimental scenarios from 10-shot to full-supervised on MIT Movie dataset and MIT Restaurant dataset to explore the two strategies.

As illustrated in Figure 5, we observe that: 1) The model performs worse in the few-shot scenarios when the synthetic tokens are used as entity types. 2) However, it is unexpected that the strategy of using synthetic tokens has superior performance than the other strategy in the rich-resource scenarios. We conjecture that 1) in the low-resource scenarios, the semantic information in the label words of the natural language form can help model stimulate latent knowledge hidden in PLMs and generate the entity words more accurately, while synthetic tokens are unable to do this. 2) However, when there are enough supervised signals, the synthetic tokens gradually learn the specific semantic relationship for a certain task, and the original semantics of label words in the natural language form would interfere with the specialization process of these words.

6 Conclusion

In this paper, we reformulate the sequence labeling task as a generation problem and propose a multi-task instruction-based generative framework (InstructionNER) for low-resource NER. By constructing source sentences with descriptive task instructions and limited answer options, InstructionNER can make the best use of semantic knowledge learned by PLMs. Moreover, we further introduce

\(^{5}\) ATIS include 79 entity types and using natural language labels directly would make the input Instruction too long.
two auxiliary tasks to enable the model to capture more boundary information of entities and semantic of types. Experiments on several NER datasets show that our method consistently outperforms other baselines, proving its effectiveness in few-shot settings.

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A Implementation Details

In this paper, we use T5 as the backbone PLM in our experiments. There are no extra parameters are introduced, so the total parameters of our model is as same as original T5. Specifically, the number of parameters of T5-base, T5-large and T5-v1.1 are 220M/770M/770M respectively. For all experiments, we train and test our model on a single V100 GPU. On average, each model required 2 GPU-hours to train. The deep learning frameworks used in this paper are Pytorch==1.7.1 and transformers==4.3.3.

B Dataset Statistics

The statistical information as shown in Table 4.

| Dataset         | Sample Account (train / test) | Entity Type |
|-----------------|-------------------------------|-------------|
| CoNLL03         | 14986 / 3684                  | 4           |
| ATIS            | 4478 / 893                    | 79          |
| MIT_movie       | 9773 / 2443                   | 12          |
| MIT_restaurant  | 7660 / 1521                   | 8           |
| Ontonotes5.0    | 115812 / 12217                | 18          |

Table 4: Statistics of mentioned NER datasets

\(^{6}\)https://huggingface.co/t5-base

\(^{7}\)https://huggingface.co/t5-large

\(^{8}\)https://huggingface.co/google/t5-v1-1-large
Figure 6: F1 score(%) on MIT Restaurant dataset with different ET+EE data sample ratios under 20/50 shot settings.

C Performance on Relatively Abundant Settings

We conduct the experiments on MIT Movie and MIT Restaurant under the setting of 100/200/500-shot. As shown in Table 5, when the data size grows to 100/200/500-shot for each entity type, the performance of InstructionNER still grows but with a relatively small increment, and even underperforms the LightNER baseline in the end. It reveals that our InstructionNER model focuses more on learning the general knowledge and is trained in the form of meta-learning. Thus, it shows high efficiency in the data-scarce scenarios. However, when the data is sufficient, the generality may hamper the model’s specialization so that adding extra samples shows limited performance improvement. We also discuss the similar conclusion in Section 5.3.

| Methods                  | MIT Movie | MIT Restaurant |
|--------------------------|-----------|----------------|
|                          | 100       | 200            | 500            | 100       | 200            | 500            |
| Baselines                |           |                |                |           |                |                |
| LC-BERT                  | 50.7      | 59.3           | 74.4           | 53.5      | 57.4           | 61.3           |
| LC-BART                  | 47.5      | 54.2           | 64.1           | 52.2      | 56.3           | 60.2           |
| Template                 | 56.3      | 62.0           | 74.9           | 60.1      | 62.8           | 65.0           |
| BARTNER*                 | 70.1      | 74.6           | 82.6           | 65.3      | 74.4           | 75.7           |
| LightNER                 | **78.0**  | **80.6**       | **84.8**       | 70.8      | 75.5           | **80.2**       |
| Our implementations      |           |                |                |           |                |                |
| InstructionNER           | 76.2      | 78.2           | 82.6           | 72.5      | 74.2           | 76.6           |
| InstructionNER_{ET}      | 76.9      | 77.7           | 82.2           | 73.3      | **76.0**       | 76.1           |
| InstructionNER_{EE}      | 76.2      | **78.4**       | 82.5           | **73.4**  | 75.9           | 76.0           |
| InstructionNER_{ET,EE}   | 74.3      | 78.4           | 82.3           | 72.7      | 75.5           | 76.6           |

Table 5: F1 score(%) on MIT datasets under 100/200/500 shot settings. **Bold** numbers indicate the best performance across baselines and our implementations, and underline indicates the best performance in baselines or our implementations. "*" indicates our reproduction results.

D The Ratio of Auxiliary Tasks

We notice that the performance is dropped when we combine the ET and EE tasks. We conjecture the reason is that the data size ratio between the main task and the auxiliary tasks is reduced to 1:2 when introducing ET and EE simultaneously, which means our model will focus more on auxiliary tasks but less on the main task, leading to a performance drop on the main NER task. To validate this, we sample different ratios of auxiliary data and conduct experiments to evaluate the F1 score. As illustrated in Figure 6, when the data of auxiliary tasks is less or equal than the main task (i.e., the sample ratio is between 0.1 and 0.5), InstructionNER can achieve a better F1 score than the one trained without auxiliary tasks (i.e., the sample ratio is 0) or with full auxiliary tasks data (i.e., the sample ratio is 1). When auxiliary tasks data grows larger than the main task (i.e., the sample ratio > 0.5), the performance drops in different degrees and sometimes even underperforms the one without auxiliary tasks.