

Formulating Few-shot Fine-tuning Towards Language Model Pre-training: A Pilot Study on Named Entity Recognition

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Abstract

Fine-tuning pre-trained language models is a common practice in building NLP models for various tasks, including the case with less supervision. We argue that under the few-shot setting, formulating fine-tuning closer to the pre-training objective shall be able to unleash more benefits from the pre-trained language models. In this work, we take few-shot named entity recognition (NER) for a pilot study, where existing fine-tuning strategies are much different from pre-training. We propose a novel few-shot fine-tuning framework for NER, FFF-NER. Specifically, we introduce three new types of tokens, “*is-entity*”, “*which-type*” and *bracket*, so we can formulate the NER fine-tuning as (masked) token prediction or generation, depending on the choice of the pre-training objective. In our experiments, we apply FFF-NER to fine-tune both BERT and BART for few-shot NER on several benchmark datasets and observe significant improvements over existing fine-tuning strategies, including sequence labeling, prototype meta-learning, and prompt-based approaches. We further perform a series of ablation studies, showing few-shot NER performance is strongly correlated with the similarity between fine-tuning and pre-training.

1 Introduction

Pre-trained language models (Peters et al., 2018; Devlin et al., 2019; Liu et al., 2019; Lewis et al., 2020) have the ability to capture extensive semantic and syntactic information in text. Such prior understanding of language offers a solid foundation to downstream tasks, therefore, fine-tuning language models have been widely applied in various NLP applications, especially when the task-specific annotations are limited (a.k.a. few-shot setting) (Radford et al., 2019; Brown et al., 2020).

While many few-shot strategies have been explored, there is no established systematic principle

on designing these strategies. Intuitively, given the same amount of task-specific annotations, a pre-training aligned fine-tuning strategy should more easily extract beneficial knowledge encoded during pre-training. Therefore, we hypothesize that the performance of few-shot fine-tuning is tied to the similarity between the fine-tuning strategy and the pre-training objective.

To verify this hypothesis, we take the Named Entity Recognition (NER) task for a pilot study, since the common fine-tuning strategies for NER are much different from popular pre-training tasks. Specifically, the most common fine-tuning paradigm for NER is to train a sequence labeling model on top of a pre-trained language model — for each token in a sentence, simultaneously decide whether it belongs to an entity and the type of the entity among given entity types. As an example showing the difference, the commonly used pre-trained language model BERT has a pre-training goal to disambiguate some masked tokens by predicting the correct token (masked language modeling). While in sequence labeling, *each* token (representation) is to decide *two* different pieces of information (span & type).

Following our hypothesis, we propose a few-shot fine-tuning framework for NER, FFF-NER as shown in Figure 1. At the core is decoupling span detection and type prediction, since they are essentially two quite different tasks, which is not easy to learn altogether in few-shot fine-tuning. We introduce two new types of tokens that we dub as “*is-entity*” and “*which-type*” to perform the two tasks individually. With the help of these two types of tokens, we consider each instance not a single sentence but a sentence-span pair and ask the model to predict whether the span is an entity and, if it is, the type of the entity. The two tokens are placed around the span. By introducing another type of token, *bracket*, around the span and the two special tokens, the sentence highlights the span in consider-

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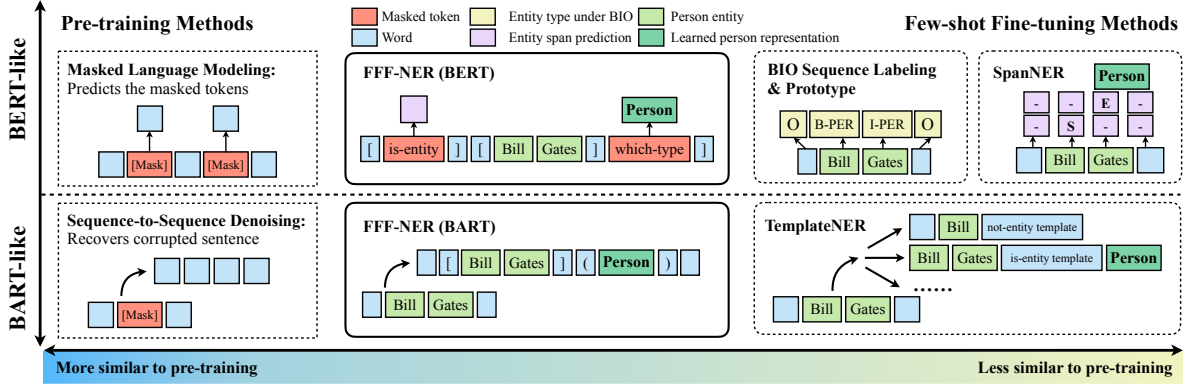


Figure 1: Two pre-training strategies (masked language modeling and sequence to sequence denoising) and different few-shot fine-tuning frameworks based on them. Our FFF-NER has different designs for different pre-trained models, but share the same principle of simulating the pre-training task.

ation and treats the special tokens as meta-data-like information. The goal of the fine-tuning task is then to classify the corresponding “*is-entity*” and “*which-type*” representation for each span.

Our FFF-NER is formulated in a pre-training agnostic way, and here we elaborate how it can be adapted to two popular pre-training tasks, (masked) token prediction and generation. For BERT trained with masked language modeling, we use the masked tokens as the two special tokens and ask the model to perform a binary classification on “*is-entity*” and a multi-class classification on “*which-type*”. For BART trained with sequence to sequence denoising that is able to generate text, the two tokens are virtual — we treat the formulated sentence with *brackets* indicating spans and type-decoded special tokens as the target clean sentence, and the original sentence as a noised one without entity information. The model is to decode the target sentence with entity information.

We conduct experiments on the recently proposed few-shot NER benchmark (Huang et al., 2021) and show that FFF-NER can achieve significant improvements over the state-of-the-art methods, including sequence labeling, prototype meta-learning models, and prompt-based approaches. It is worth mentioning that several recent NER methods (Cui et al., 2021; Yang and Katiyar, 2020; Wang et al., 2021; Ma et al., 2021) have different experimental settings and dataset/data-split selections (even though the dataset names may be the same). Therefore, for a fair comparison, we have carefully re-evaluated them under the same setting.

Our extensive ablation studies have further verified the correlation between the performance of NER and the similarity between fine-tuning and pre-training. Focusing on the masked language

modeling pre-training task, the key efforts that we made in FFF-NER to close the gap between pre-training and fine-tuning (i.e., the usage of *mask*, *brackets*, “*is-entity*”, and “*which-type*” tokens) are all crucial to the NER performance.

All these empirical results are in favor of our hypothesis, shedding insights on design principles for fine-tuning strategies. Remarkably, there are existing models GENRE (Cao et al., 2021) and TANL (Paolini et al., 2021) sharing the same design principle as FFF-NER by formulating BART fine-tuning as a token generation task. They can be viewed as siblings of FFF-NER, serving as another strong evidence in favor of our hypothesis. Our contributions are summarized as follows.

- We hypothesize for better performance, (few-shot) fine-tuning should be designed similarly to the pre-training as much as possible. We further conduct an ablation study to verify this insight.
- Our pilot study on few-shot NER shows favorable results for our hypothesis. Specifically, we propose a fine-tuning framework for few-shot NER FFF-NER, which outperforms sequence labeling, protocol methods, and prompt-based learning models on the five benchmark datasets for few-shot NER.
- We enrich the standard few-shot NER benchmark by including more state-of-the-art methods.

Reproducibility. We will release our code on GitHub¹.

2 Related Works

2.1 Named Entity Recognition

It has been shown that traditional fine-tuning methods that work in full supervision might not work

¹<https://github.com/ZihanWangKi/ffner>

well in few-shot learning scenarios (Wang et al., 2021), as is the case in widely used BIOES-style sequence labeling and near state of the art fully supervised NER models (Li et al., 2020). Some works have been proposed based on templates or prototypical networks targeting low resource NER (Cui et al., 2021; Yang and Katiyar, 2020; Wang et al., 2021). However, there lacks a general principle for few-shot NER. In this work, we claim that the similarity between the fine-tuning task and pre-training task can help few-shot learning and prove empirically with our pre-training tailored few-shot fine-tuning design and several ablations.

2.2 Prompt Learning

Recently, a resource-less way of solving downstream tasks, prompt learning (Liu et al., 2021) has gained interest. By stirring knowledge from pre-trained language models with manually designed templates, the GPT model (Radford et al., 2019; Brown et al., 2020) can achieve decent performance on downstream tasks without training. For NER, since the labeling task is unseen in natural text, prompt-based methods are often combined with further fine-tuning (Cui et al., 2021). Our idea goes along the same line, where we argue that the similarity to the pre-training task can help the model better transfer knowledge from pre-training to the fine-tuning task. We show that some templates (Cui et al., 2021) might not work well for sequence-to-sequence denoising trained models, as they are still much different from the pre-training task.

3 Preliminaries

3.1 Problem Definition

The task of Named Entity Recognition is to extract the n -grams in the text that are named entities and label them with a set of pre-defined entity types. Formally, given a sequence of words $w_1, w_2, \dots, w_n$ of length n , the goal is to identify the spans $w_l, w_{l+1}, \dots, w_r$ where $l \leq r$ that is an entity, and assign it an entity type c from a set of pre-defined entity types C (e.g., $C = \{\text{Person, Location, etc}\}$). In this work, we sometimes use $l \dots r$ to denote the span for simplicity.

Metric. The most widely used metric for NER is the (span-based, micro) F_1 score. It considers all typed spans in the ground truth and from the model’s prediction and calculates its F_1 score on retrieving the whole entities.

Few-shot. There are different definitions of Few-shot learning for NER. In this work, we focus on the N -way K -shot setting (Huang et al., 2021), where we consider all $N = |C|$ entity types and for each entity type, randomly pick K sentences with supervision that contains the particular entity type. This is to make a fair comparison with the traditional sequence labeling methods since full supervision of sentences is crucial. Undoubtedly, while we select $N * K$ sentences as supervision, the total number of entity spans in the sentences can be greater than $N * K$. Therefore, it is important to evaluate all models on the same randomly selected sets of sentences. And one major reason for us choosing this setting is the established benchmark over ten NER datasets (Huang et al., 2021).

3.2 Pre-trained Language Model

The use of a pre-trained language model has become ubiquitous in NLP. By training with self-supervision, often through disambiguating corrupted sentences, pre-trained language models can obtain a general understanding of the text. Studies have shown that the pre-training task is more a major factor for downstream task performance, rather than the architecture (Tay et al., 2022).

BERT (Devlin et al., 2019) is a transformer (Vaswani et al., 2017) encoder model trained with masked language modeling. After replacing some tokens with a special mask token, the model attempts to recover the original tokens. Thus, BERT can leverage the nearby context of the mask token to predict its origin.

BART (Lewis et al., 2020) is a transformer encoder-decoder model trained with sequence to sequence denoising. The whole sentence is corrupted by replacing segments with masks, and the model is to recover the original uncorrupted sentence. A BART can predict the complete, clean sentence given a partial sentence.

4 Our Framework FFF-NER

In this section, we introduce our framework FFF-NER, and specifically talk about how to adapt it for a masked language modeling and sequence to sequence pre-trained model.

4.1 Task Formation

The goal is to design a fine-tuning task equivalent to NER and similar to pre-training, where the goal is to disambiguate sentences. We consider each

possible span in a sentence and predict whether it is an entity and, if it is, the type of it. The major difference from our task to a traditional sequence labeling task is that we decouple the span detection and entity prediction problems.

We introduce two tokens, “is-entity” and “which-type” for span detection and type prediction. For a particular sentence and a span specified, we insert the two tokens around the span and then brackets around the two tokens and the span. As an illustration, suppose the sentence in consideration is

Tom lives in Los Angeles

and the span is “Los Angeles”, then our task translates (by inserting 6 brackets and 2 special tokens) the sentence into

Tom lives in [is-entity] [Los Angeles] [which-type]

The brackets “highlight” the two special tokens and the span in the sentence, which are important for understanding whether the span is an entity and the type of it. The brackets may also hint that the special tokens should be treated as meta-data, instead of normal text.

Different pre-trained language models will have slightly different training objectives and prediction strategies based on such a task formation. We will focus on the two popular pre-trained language models, BERT and BART, and talk about integrating them with the framework.

4.2 Instantiation of FFF-NER using BERT

We first talk about BERT, an encoder model pre-trained with masked language modeling.

Model Architecture. We use the BERT model to encode the translated sentence. Then, the last layer representations for the two special tokens are extracted, and each is fed through a classification head to retrieve the class logits for both span detection and type prediction. The pre-trained model is also tuned (i.e., the parameters are not frozen), as in many fine-tuning approaches. We use the mask token for both “is-entity” and “which-type”.

Training. We train the model to detect whether the span is an entity and predict the entity type for each span sentence pair. We consider a negative sampling approach to treat the given entities as positive instances and all the other spans as potential negative ones. Specifically, for each sentence $W = w_1, w_2, \dots, w_n$ with typed entity spans

$\mathcal{E}_W = \{(l_1, r_1, t_1), (l_2, r_2, t_2), \dots, (s_e, r_e, t_e)\}$ that are given as supervision, we consider a “positive” loss for the sentence and a certain entity span

$$\mathcal{L}^{\text{pos}} = \mathcal{L}(\text{is-entity}) + \mathcal{L}(\text{which-type}),$$

where $\mathcal{L}(\text{is-entity})$ is the cross-entropy loss for the binary prediction problem of classifying the “is-entity” token, and $\mathcal{L}(\text{which-type})$ is the cross-entropy loss for the multi-class prediction problem of classifying the exact type. The “negative” loss is learned on spans that are not entities. For the sentence W , there are $|W| + \binom{|W|}{2} - |\mathcal{E}_W|$ spans that are not entities. We consider sampling a subset $\mathcal{D}_W$ of negative spans for each sentence every epoch. The sample can change every epoch, which gives high coverage over all the negative spans. Then, for each negative span, the loss is

$$\mathcal{L}^{\text{neg}} = \mathcal{L}(\text{is-entity}).$$

Here, we only consider the is-entity loss since there is no entity type for the sampled negative span.

During training in each epoch, we first sample all the negative samples along with the positive ones, treat it as the dataset to train on in the epoch, and perform regular (mini-)batch gradient descent on the dataset with the loss.

$$\mathcal{L} = \mathcal{L}^{\text{pos}} + \mathcal{L}^{\text{neg}}.$$

Negative Sampling for Training. Here, we detail how we sample the negatives during training. There are two things to consider, the number of negative samples to pick and the probability of each span being sampled as a negative.

Directly training on all negative samples is very hard, since there are much more negatives than positives, resulting in an imbalanced training set. We describe how we determine the number of negatives to pick: the number of negative samples depends on the length of the sentence and the number of entities given as supervision in it. Intuitively, the longer the sentence is, the more negative spans we need to pick to cover every token that appears in it. And the more entities in the sentence, the more negative spans we need to pick to cover overlapping non-entities with the entities. We consider these two measurements separately.

For sentence length, we consider $\alpha * |W|$ negative samples where α is a small constant. This is based on a statistical result where $O(|W| \log |W|)$ randomly sampled spans can cover each word with

high probability, and an empirical reasoning that since sentences are short, even after removing the log factor, the sampled spans still can cover almost all words in expectation.

We then take a simple approach where we *project* entities as virtual words that increases the length of the sequence; then, we fall back to the formula proposed for the sentence lengths. Based on statistics in the CoNLL (Sang and Meulder, 2003) training set, the ratio of tokens to the number of entities is about 10 : 1. We count each entity as 10 words and select $\alpha * 10 * |\mathcal{E}_W|$ negative samples.

Finally, we sum up these two numbers as the negative samples for each sentence. We empirically show that this choice works well, and through sensitivity studies, the choice of α is not significant to performance changes.

We also note that since we only sample a portion of negatives, we should consider a weighted sampling since there are important negatives: those that have high overlap with a true entity (e.g., “Chicago is” and “York”). The model learns spurious features without explicitly treating them as negatives.

To solve this, for each sentence, we define a sampling probability based on the overlap between the non-positive spans and entities. If the span contains words $w_l, w_{l+1}, \dots, w_r$, and among these $r - l + 1$ words, c of them are within an entity in the sentence, the probability for the span being sampled is proportional to $\exp(\frac{c}{r-l+1})$. The probability of each sample is determined based on the intuition that the hard instances to predict are those that look like an entity. Therefore, we calculate the overlap between the span and the entities, normalized by the length of the span to assign a priority score for each span. Simply treating this score (after normalizing to a distribution) as the probabilities to sample will cause the sampling process never to pick spans that have no intersection with entities since their priority score is 0. So, we transform the percentage into an exponential scale and normalize thereafter to form a probability distribution.

Predicting. During prediction, we enumerate through all spans in the sentence and extract the probability of it being classified as an entity $p_{l,r}$ (from the “is-entity” token), along with the type (the class that has the maximum probability on *which-type* token). Ideally, all the spans with $p_{l,r} \geq 0.5$ should be disjoint since all our positive instance training is performed on non-overlapping spans from a non-nested NER dataset. However,

training is hard to be perfect, especially in few-shot scenarios. Therefore, we need a strategy to resolve the overlapping predicted spans.

We consider the most straightforward way to resolve overlaps: greedily assign spans based on their probability and ignore overlapping ones with lower probability. Formally, we consider all spans (l, r) with $p_{l,r} \geq 0.5$ and sort them with the largest probability one first. Then, we pick the spans one by one and add them to the final predicted entity list, given that the span does not overlap with an already picked span, in which case we ignore it and move on to the next span.

4.3 Instantiation of FFF-NER using BART

MLM pre-training is not the only type of model that can be tuned under our setting. We talk about instantiating our framework with an encoder-decoder model pre-trained with sequence to sequence denoising, BART.

Setup The sequence denoising task is to recover the original sentence given a partially corrupted version. As a direct simulation of the MLM-based setting for FFF-NER, we can consider the original sentence as partially corrupted, and ask the model to generate the full sentence that contains the decoded “is-entity” and “which-type” tokens indicating the span and type. However, in sequence decoding, the “is-entity” part is unnecessary since the brackets are generated to predict the span. We illustrate the sentence denoising setup with an example. Consider an input sentence

Tom lives in Los Angeles

then, a correctly decoded sentence is

[Tom] [Person] lives in [Los Angeles] [Location]

We introduce two similar designs in literature. **GENRE.** GENRE (Cao et al., 2021) was originally proposed for entity linking. The setup is almost equivalent to our setup above except for the use of different type of brackets.

TANL. TANL (Paolini et al., 2021) has a slightly different design that joints the adjacent brackets between the entity and the type with a “|”. For the same input sentence example in the setup section, the correctly decoded sentence is

[Tom | Person] lives in [Los Angeles | Location]

Because of the existence of such work, our experiments will focus on the MLM-based models and we leave discussion of such sequence-to-sequence models in the Appendix.

Dataset	LC	P	FFF-NER
CoNLL	53.5	58.4	67.90 (± 3.95)
Onto	57.7	53.3	66.40 (± 1.62)
WikiGold	47.0	51.1	61.42 (± 8.82)
WNUT17	25.7	29.5	30.48 (± 3.69)
MIT Movie	51.3	38.0	60.32 (± 1.12)
MIT Restaurant	48.7	44.1	51.99 (± 2.33)
SNIPS	79.2	75.0	83.43 (± 1.44)
ATIS	90.8	84.2	92.75 (± 0.99)
Multiwoz	12.3	21.9	47.56 (± 8.46)
I2B2	36.0	32.0	49.37 (± 5.08)
Average	50.2	48.8	61.15

Table 1: Experiments on N-way 5 shot NER on all datasets in Huang et al. (2021) for our model. LC stands for a sequence labeling method, P stands for prototypical network, and FFF-NER is a BERT-base-uncased model trained with our framework. We bold the best scores that are statistically significant when compared with others at a 0.05 significance level.

5 Experiments

5.1 Compared Methods

We compare with several publicly available low-resource NER models.

Roberta-base is a sequence labeling model build on the official roberta-base (Liu et al., 2019). It is a baseline result reported in Huang et al. (2021). We also use BERT models and experiment with **BERT-{base, large}-{uncased, cased}**.

Nearest Neighbor is a baseline prototype method reported in Huang et al. (2021) that assigns each token representation to the nearest label representation, learned by the examples in the training set in a prototypical network (Snell et al., 2017).

StructShot (Yang and Katiyar, 2020) extends Nearest Neighbor to consider label transitions as in a Conditional Random Field (Lafferty et al., 2001).

TemplateNER (Cui et al., 2021) considers templates that are human selected formatted like “X is a Y entity .” and “X is not a named entity .” where X is the span to consider and Y is the ground truth entity during training. It uses BART to decode the template for each sentence span pair.

EntLM (Ma et al., 2021) also has the idea of minimizing the gap between pre-training and fine-tuning. They asked a MLM-pretrained language model to predict every token in the input sentence. The prediction should either be within list of special tokens specifying each type if it is an entity

or the original token itself otherwise. This setting draws the pre-training and fine-tuning closer by making token predictions, but poses another difference in that the target predicted word might not suit the context well. In fact, they need to specially curate a list of entity names. More discussions on this are in the Appendix.

SpanNER (Wang et al., 2021) is a method that also breaks span detection and type prediction into two tasks. For each token, they simultaneously predict whether it is a start of span and an end, similar to question answering. Then, they utilize class descriptions from annotation guidelines or Wikipedia to construct a class representation to match the detected spans. In some sense, their ideology follows our framework, as an important step in our framework is also decoupling span detection and type prediction. However, many of their model designs still differ from the backbone pre-trained model BERT (e.g., asking each token to perform span predictions and averaging span representations to find the closest class representation).

5.2 Experimental Settings

For the four BERT sequence labeling models, we use the implementation of sequence labeling in Huggingface (Wolf et al., 2020; Huggingface, 2022), and tune the number of epochs to use.

We reproduce the other compared methods as their performance is not reported on the standard few-shot setting/standard datasets or splits in Huang et al. (2021). When reproducing, we follow the original hyper-parameters except (1) Increasing the sequence length when necessary, (2) Decreasing the batch size if the GPU memory does not fit, and (3) Tuning the number of training epochs and learning rate if performance is not desirable.

Our masked language modeling based FFF-NER is built with Pytorch Lightning (PyTorchLightning, 2022). We try to follow all hyper-parameter settings (optimizer, learning rate, etc.) as close as Huggingface’s sequence labeling.

All experiments are conducted on RTX A6000 and RTX 8000 GPUs, both having 48 GB GPU RAM. For exact hyperparameter settings, please refer to the Appendix.

5.3 Datasets

We mainly experiment on five of the ten datasets in Huang et al. (2021). The reasons of choosing these five datasets are: (1) SpanNER (Wang et al., 2021) require descriptions that were not gathered

Framework	Language Model	CoNLL	Onto	WNUT17	MIT Movie	MIT Restaurant
Seq Labeling	Roberta-base [†]	53.5	57.7	25.7	51.3	48.7
	BERT-base-uncased	52.92 (± 4.55)	56.66 (± 0.85)	21.53 (± 4.81)	47.29 (± 1.32)	45.64 (± 2.30)
	BERT-base-cased	51.04 (± 3.94)	60.71 (± 1.11)	20.18 (± 5.43)	44.98 (± 1.48)	39.07 (± 2.73)
	BERT-large-uncased	53.50 (± 4.40)	59.65 (± 1.87)	28.03 (± 5.08)	52.84 (± 2.00)	47.33 (± 1.91)
	BERT-large-cased	52.23 (± 3.90)	64.03 (± 1.28)	26.76 (± 4.30)	48.31 (± 2.93)	43.08 (± 1.98)
Prototype	Roberta-base [†]	58.4	53.3	29.5	38.0	44.1
TemplateNER	BART-large	61.46 (± 6.46)	N/A	11.20 (± 1.09)	41.80 (± 1.36)	N/A
StructShot	BERT-large-cased	50.55 (± 7.75)	69.80 (± 1.19)	27.32 (± 3.01)	56.58 (± 2.01)	45.62 (± 3.39)
EntLM [‡]	BERT-base-cased	61.67 (± 2.72)	67.97 (± 1.24)	23.70 (± 4.03)	43.95 (± 0.79)	51.29 (± 2.12)
	BERT-large-cased	59.44 (± 2.85)	68.92 (± 1.58)	17.82 (± 3.06)	45.31 (± 6.09)	53.13 (± 1.56)
SpanNER [‡]	BERT-base-uncased	58.95 (± 4.15)	67.89 (± 1.33)	22.18 (± 4.63)	55.79 (± 1.22)	52.08 (± 2.46)
	BERT-large-uncased	57.93 (± 3.99)	68.40 (± 1.39)	20.72 (± 6.58)	57.81 (± 2.29)	50.10 (± 1.06)
FFF-NER	BERT-base-uncased	67.90 (± 3.95)	66.40 (± 1.62)	30.48 (± 3.69)	60.32 (± 1.12)	51.99 (± 2.33)
	BERT-large-uncased	69.23 (± 3.90)	69.43 (± 1.30)	34.96 (± 5.07)	61.31 (± 2.12)	55.01 (± 2.71)

Table 2: Experiments on N-way 5 shot NER on 5 datasets. The average performance over ten different folds of seed shots are given, and the standard deviation is given in parentheses. [†] indicates results borrowed from Huang et al. (2021), and they did not report standard deviations. N/A indicates the performance is far behind other methods, and we suspect that extensive dataset-specific template/hyperparameter tuning is necessary. For the backbone language model, we show the better one among the cased and uncased versions. We discuss the reproduction details and number differences from reported numbers of EntLM and SpanNER in the Appendix.

for the other five datasets (2) These five datasets are commonly used and cover various domains (news, general, social media, reviews). We do include a study of our framework on all of the ten datasets. For each dataset, we run on the standard ten splits from Huang et al. (2021) whenever possible and report both the average and standard deviation.

5.4 Performance of FFF-NER

In Table 1 we show the performance of our framework on a BERT-based-uncased model on all ten datasets in Huang et al. (2021) and compare with the two baselines that do not require extra data: sequence labeling and prototype. We see that our model performs statistically significantly better than the compared methods on every dataset except WNUT17. We also note that our overall performance on the ten datasets exceeds the best method reported in Huang et al. (2021) (LC + NSP + ST) that has an average performance of 58.5. Notably, we do not require a large-scale noisy fine-grained entity recognition dataset to adapt the pre-trained language model or self-training on the unlabeled in-domain dataset.

In Table 2 we show the full table containing our method and all the compared methods on the five datasets performing 5-shot NER, differentiating by the underlying pre-trained language model.

Framework	CoNLL	MIT Restaurant
Sequence Labeling	52.92 (± 4.55)	45.64 (± 2.30)
FFF-NER	67.90 (± 3.95)	51.99 (± 2.33)
Not mask	64.08 (± 3.62)	52.71 (± 3.47)
No brackets	60.18 (± 3.42)	42.73 (± 4.21)
Span & type together	53.20 (± 7.96)	33.79 (± 6.87)

Table 3: Ablations of FFF-NER that distance the fine-tuning task from pre-training. We use a BERT-base-uncased model.

Each baseline performed pretty well on some of the datasets, especially EntLM and SpanNER, which we attribute to their unanimous design of bridging pre-training and fine-tuning. However, none of them showed consistent improvement across all datasets like ours. When looking at the absolute scores, our large methods are statistically significantly better than the compared methods on all datasets except Onto.

5.5 Ablations of FFF-NER

We strengthen our claim that the improvement of our method comes from the fine-tuning design being similar to the pre-training task. We consider three variants of our framework design for masked language modeling and show the results in Table 3. **Not mask** replaces the mask token used for the two special tokens with the actual tokens “span” and “type”. We can see that the performance drops sig-

Backbone	BERT	BART
Sequence Labeling	52.92 (± 4.55)	59.66 (± 2.92)
FFF-NER for MLM	67.90 (± 3.95)	59.65 (± 2.61)

Table 4: An experiment where FFF-NER for Masked Language Modeling trained models (e.g., BERT) are applied to Sequence Denoising trained models (e.g., BART).

nificantly on CoNLL, while no significant changes can be observed from Restaurant. We attribute this to the fact that there is less difference from a mask token to an actual token for pre-trained language models since MLM is also trained on non-mask tokens for 20% of the training time (Devlin et al., 2019). However, the slight decrease in performance still indicates that using the mask token is better.

No brackets removes all six brackets when formulating the input sentence. Since we have the two mask tokens around the span, the input sentence is still distinct for different spans. However, the performance drops by a large margin. At first, this may sound intriguing since the sentence without brackets looks more like natural text. However, we note that with the original setting with brackets, the sentence is like annotating a span with meta-data, while without brackets, the model is to complete the sentence with missing words.

Span & type together removes the “is-entity” token and integrates the span detection and type prediction task. The “which-type” token now needs to perform two tasks simultaneously, much like in sequence labeling. The performance on the two datasets drops drastically: on CoNLL, the performance is similar to that of sequence labeling, and on MIT Restaurant, the performance is even lower.

5.6 A Mismatched Scenario of FFF-NER

Given our hypothesis that pre-training fine-tuning gap should be minimized, one would expect that a framework designed to reduce the gap between MLM pre-training shouldn’t work well for Sequence Denoising pre-training. We show that this is indeed the case with an experiment in Table 4. Even though FFF-NER outperforms Sequence Labeling on an MLM model, as expected, it does not show a difference on a model with a different pre-training objective. This observation can be even strengthened if we can check the other way – whether Sequence Denoising tailored methods fall short on MLM pre-trained models. However, we note that all such methods we tested in this work

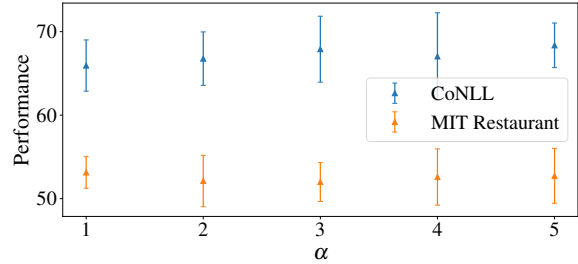


Figure 2: Sensitivity study using on CoNLL and MIT Restaurant using BERT-base-uncased. Average performance and standard deviation are shown.

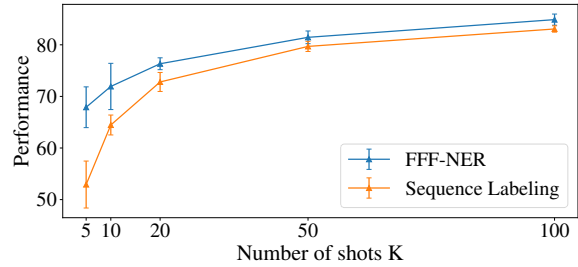


Figure 3: Analysis of our FFF-NER when the number of shots vary on the CoNLL dataset using BERT-base-uncased. Average performance and standard deviation are shown. A sequence labeling model is also shown for comparison.

require the ability to generate text, which MLM models can not.

5.7 Sensitivity Study of FFF-NER

We study the choice of the number of negative spans to sample in Figure 2. In our framework, we sample $\alpha * (|W| + |\mathcal{E}_W| * 10)$ negative spans for each sentence, and α is chosen to be 3 across all datasets. While we fix the use of 10, we analyze how the performance varies with different choices of α . We can see that overall, the performance is pretty steady even when we use two times smaller number of samples ($\alpha = 1$) or almost one time more number of samples ($\alpha = 5$). Therefore, we believe that one does not need extensive hyper-parameter selection on α .

5.8 Performance vs Shots

We also study how our framework works with more supervision. In Figure 3 we increase the number of shots K from the default 5 shots to as many as 100 shots. A clear trend is that the advantages of our framework vanish as the number of shots increases. We also train FFF-NER with BERT-base-uncased on the full CoNLL dataset, achieving a performance of 95.57 on the dev set and 92.06 on the test set. This result is

slightly less but close to a sequence labeling based BERT model. The vanishing performance in high-resource scenarios aligns with our common sense — the gap between pre-training and fine-tuning can be overcome when there is large amounts of supervision. Overall, our framework is still capable of handling large amounts of supervision, albeit designed for a few-shot scenario.

6 Conclusions

In this work, we draw attention to an intuitive principle for few-shot fine-tuning designs: the closer the fine-tuning task is to the pre-training task, the better the performance. We empirically prove this by designing a few-shot fine-tuning framework for NER, FFF-NER. Our framework is not constrained to a specific architecture of language models and can be easily extended to distinct pre-trained models (e.g., BERT and BART in our experiments). Our model outperforms existing fine-tuning strategies including sequence labeling, prototype meta-learning, and prompt-based approaches on the standard benchmark for few-shot NER. Through a series of ablations, we also show that if we manually remove ingredients in our framework that make the fine-tuning task similar to pre-training, the performance drops.

We see future works in two directions. One is to incorporate label semantics into the BERT based FFF-NER, so that even less supervision can suffice. The other is to verify our principle of few-shot fine-tuning on other downstream tasks.

Ethical Considerations

The work presented in this paper deals with design principles in the few-shot scenario. We present experiments on Named Entity Recognition, which do not pose ethical concerns. Further, we will also open source our code. Our framework makes it possible for training NER models with small amounts of supervision, which makes NER tools more accessible to every ordinary people, so we are on the positive side on ethical consideration.

Limitations

Time Complexity. One drawback of our FFF-NER design for MLM models is the increased time complexity. Compared to a sequence labeling method which needs one forward pass to predict entities of the whole sentence, our requires poten-

tially $n + \binom{n}{2}$ passes. However, a few things to note is:

- If one has prior knowledge on how long the entity could be, they can only consider spans with at most that length and avoid the quadratic dependency on the sequence length.
- In few-shot learning, the training set is small, so the increase in training time is insignificant.

Yet, even with these considerations, our work is less efficient than approaches that require a single pass for each sentence, like the traditional sequence labeling method.

Special Treatment for Large Training Sets.

Shown in the Appendix, our method needs a smaller learning rate when we experiment with more data (e.g., 100 shot scenario). Otherwise, there will be cases when the model training fails due to gradient vanishing. We also observed this behavior for EntLM (Ma et al., 2021) and tuned the learning rate for it as well. We do not think that this problem is severe since (1) they are noticeable without a development set as one can check the gradients and the training accuracy/loss to detect such problems and (2) decreasing learning rate or restarting with different initializations can resolve this problem in our experiments.

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A FFF-NER for MLM

We include some pseudo code pieces to help understand the whole framework when applied to masked language modeling based pre-training language model.

Algorithm 1: Create

Input: Sentence W and entities $\mathcal{E}_W$.
 $\mathcal{E}_W =$ all spans not in $\mathcal{E}_W$.
if *is predicting* **then**
 Return Formulated Input for
 $(W, e), \forall e \in \mathcal{E}_W \cup \overline{\mathcal{E}_W}$.
else
 $S(\overline{\mathcal{E}_W}) =$ sampled $\overline{\mathcal{E}_W}$.
 Return Formulated Input for
 $(W, e), \forall e \in \mathcal{E}_W \cup S(\overline{\mathcal{E}_W})$.

Algorithm 2: Training

Input: Few-shot Training Dataset D_{train} ,
Model $\mathcal{M}$.
for each epoch do
 $\overline{D_{train}} = \emptyset$
 for each $(W, \mathcal{E}_W)$ **in** D_{train} **do**
 $\overline{D_{train}} = \overline{D_{train}} \cup \text{Create}(W, \mathcal{E}_W)$
 Train $\mathcal{M}$ on $\overline{D_{train}}$.
Return $\mathcal{M}$

Algorithm 3: Predicting

Input: Evaluation Dataset D_{eval} , Model
 $\mathcal{M}$.
Final predictions $\mathcal{P} = \emptyset$
for each $(W, \mathcal{E}_W)$ **in** D_{eval} **do**
 $\text{preds} = \mathcal{M}(\text{Create}(W, \mathcal{E}_W))$.
 $\mathcal{P} = \mathcal{P} \cup \text{Resolve predictions } \text{preds}$.
Return $\mathcal{P}$

B Dataset Statistics and License

We refer the readers to the benchmark paper that standardized the datasets (Huang et al., 2021).

C Hyperparameters

We show the hyper-parameters we use for training the sequence labeling model and FFF-NER based on BERT in Table 5 for both base and large models. We note that there are some exceptions on learning rates for our framework. For the base models when experimenting with 100 shots, we set the learning rate to 0.00001; for the fully supervised training, we set the learning rate to 0.000002. For the large

	Sequence Labeling	FFF-NER-BERT
Epochs	100/300 (base/large)	30
Optimizer	AdamW	
Learning Rate	0.00002	†
Scheduler	Linear, no warmup	
Batch Size	32	
Dropout	0.1	
α	N/A	3

Table 5: Hyper-parameters for sequence labeling and FFF-NER-BERT, for all experiments in the paper. † there is some exceptions for the learning rate, explained in text in Section C.

models on the Onto dataset, we set the learning rate to 0.00001.

D EntLM

EntLM needs to identify representative tokens for each class. In their paper, they follow BOND (Liang et al., 2020) that labels the training set based on distant supervision from external knowledge bases. However, BOND was not developed for all the datasets in the benchmark, so we take an alternative approach where we give EntLM *ground truth* full training set to find representative tokens.

Arguably, this should be an upper bound for EntLM since we replaced a noisy source to a clean source. However, we note that there is a performance difference of our reproduced EntLM from their paper. We ruled out the differences between theirs and ours in Table 6. We can see that while there is a difference emerging from the backbone model choice to our surprise, there is a performance drop when the source of labels comes from ground truth instead of a noisy distant supervision-based approach. We show the representative words in Table 7 and note that the actual tokens selected are rather similar for the two approaches. We argue that EntLM might suffer from instability issues where a few small changes on the representative tokens (in our case, even trying to improve it with the ground truth source) can hurt the performance quite hard.

E SpanNER

Our reproduction of SpanNER on CoNLL2003 and MitMovie with 5-shot supervision is quite different from their original numbers. There are a few

Result Source	Model	Label Source	CoNLL
reported	RoBERTa-base	Knowledge Base	68.6
reproduced	RoBERTa-base	Knowledge Base	68.40 (± 3.00)
reproduced	RoBERTa-base	Ground Truth	65.20 (± 3.03)
reproduced	BERT-base-cased	Ground Truth	61.67 (± 2.72)

Table 6: Reported and Reproduced numbers of EntLM with different model and label sources.

Source	Person	Organization	Location	Miscellaneous
Distant Supervision	"Michael", "John", "David", "Thomas", "Martin", "Paul"	"Corp", "Inc", "Com- mission", "Union", "Bank", "Party"	"England", "Germany", "Australia", "France", "Russia", "Italy"	"Palestinians", "Rus- sian", "Chinese", "Dutch", "Russians", "English"
Ground Truth	"John", "Michael", "David", "Paul", "Thomas", "Mark"	"Corp", "National", "Inc", "Commission", "St", "Co"	"Australia", "France", "Germany", "England", "Italy", "Russia"	"German", "Australian", "British", "American", "European", "Israeli"

Table 7: Representative tokens for classes in EntLM

reasons behind this:

- The dataset, particularly the labeling schema, of MiTMovie is different, while they used the same dataset names.
- The choice of 5-shot supervision is likely different due to randomness. We followed the exact same splits in [Huang et al. \(2021\)](#).
- We reported average and std performance across 10 different random 5-shot supervision, while SpanNER reported average and std performance across 5 different model random initializations. The high variance we reported indicates that different choice of splits can lead to drastically different performance.

We believe that our choice of the following [Huang et al. \(2021\)](#) has two advantages. First, this setting (datasets and data split) is open-sourced and can be compared with future work more easily. Second, the averaging across random splits make the result more stable since it accounts for the larger portion of the variance.

F Sequence Denoising Pre-training

We show the performance for models based on sequence denoising pre-trained models in Table 8. We use GENRE and TANL to illustrate how FFFNER works with BART since they are similar by design. We note that it is quite hard to compare across different pre-training models, but both GENRE and TANL have established a strong performance improvement against the TemplateNER baseline and the sequence labeling and prototype baselines in [Huang et al. \(2021\)](#).

Framework	Language Model	CoNLL	Onto	WNUT17	MIT Movie	MIT Restaurant
Seq Labeling	Roberta-base [†]	53.5	57.7	25.7	51.3	48.7
Prototype	Roberta-base [†]	58.4	53.3	29.5	38.0	44.1
FFF-NER	BERT-base-uncased	67.90 (± 3.95)	66.40 (± 1.62)	30.48 (± 3.69)	60.32 (± 1.12)	51.99 (± 2.33)
	BERT-large-uncased	69.23 (± 3.90)	69.43 (± 1.30)	34.96 (± 5.07)	61.31 (± 2.12)	55.01 (± 2.71)
TemplateNER	BART-large	61.46 (± 6.46)	N/A	11.20 (± 1.09)	41.80 (± 1.36)	N/A
FFF-NER (GENRE)	BART-base	58.86 (± 1.78)	56.12 (± 0.87)	26.98 (± 1.64)	52.45 (± 2.01)	43.34 (± 1.41)
	BART-large	71.00 (± 2.67)	64.40 (± 2.88)	41.48 (± 1.58)	53.25 (± 1.99)	51.00 (± 1.52)
FFF-NER (TANL)	BART-base	59.05 (± 1.65)	62.13 (± 0.97)	34.24 (± 3.13)	55.61 (± 1.42)	56.76 (± 2.47)
	BART-large	60.32 (± 2.47)	63.17 (± 1.26)	36.98 (± 1.37)	58.23 (± 1.37)	59.84 (± 2.27)
	T5-base	62.33 (± 2.76)	69.27 (± 1.40)	33.80 (± 2.91)	56.46 (± 1.49)	58.85 (± 1.33)

Table 8: Experiments on N-way 5 shot NER on 5 datasets. The average performance over ten different folds of seed shots are given, and the standard deviation is given in parentheses.