Robustness of Demonstration-based Learning Under Limited Data Scenario

Hongxin Zhang[1], **Yanzhe Zhang**[2], **Ruiyi Zhang**[3], **Diyi Yang**[4]
[1]Shanghai Jiao Tong University, [2]Georgia Institute of Technology
[3]Adobe Research, [4]Stanford University
[1]icefox@sjtu.edu.cn, [2]z_yanzhe@gatech.edu
[3]ruizhang@adobe.com, [4]diyiy@cs.stanford.edu

Abstract

Demonstration-based learning has shown great potential in stimulating pretrained language models' ability under limited data scenario. Simply augmenting the input with some demonstrations can significantly improve performance on few-shot NER. However, why such demonstrations are beneficial remains unclear since there is no explicit alignment between the demonstrations and the predictions. In this paper, we design pathological demonstrations by gradually removing intuitively useful information from the standard ones to take a deep dive of the robustness of demonstration-based sequence labeling and show that (1) demonstrations composed of random tokens still make the model a better few-shot learner; (2) the length of random demonstrations and the relevance of random tokens are the main factors affecting the performance; (3) demonstrations increase the confidence of model predictions on captured superficial patterns. We have publicly released our code at `https://github.com/SALT-NLP/RobustDemo`.

1 Introduction

Current large pretrained language models (PLMs) struggle to learn NLP tasks under limited data scenarios (Devlin et al., 2019; Liu et al., 2019; Lewis et al., 2020; Xie et al., 2020; Huang et al., 2021). In contrast, humans can solve natural language tasks with only a few illustrative examples(Lake et al., 2015). Motivated by this, demonstration-based learning has been introduced to augment the input with a few examples and labels. For instance, Brown et al. (2020) simply picked up to 32 randomly sampled instances and directly concatenated them with the input to perform *in-context learning* with the model frozen and significantly boosted the performance. Lee et al. (2022) concatenated the input with task demonstrations to create augmented input and fed them into PLMs to obtain improved token representations to do sequence labeling in a classifier-based fine-tuning way.

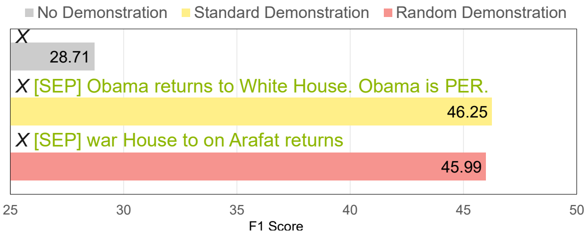

Figure 1: **Performance for different demonstrations on CoNLL03 5-shot support set.** Here X denotes the input sentence, such as "Jobs was born in America.", and we show the PER part of the whole demonstration in applegreen for visualization. Surprisingly, random tokens can be good demonstrations too.

However, how and why such demonstrations help remains unclear. As such, there has been a growing amount of work investigating the robustness and interpretability of demonstration-based learning. For instance, Lu et al. (2021) reported that few-shot text classification is very sensitive to the ordering of the demonstrations in in-context learning. On a wide range of low-resource Natural Language Understanding (NLU) tasks, Min et al. (2022b) investigated why demonstrations in in-context learning can bring performance gains over zero-shot inference and found that correct input-label mapping matters very little.

Building on these prior works, we take a deeper dive into the robustness of demonstration-based learning (Lee et al., 2022), especially for structured prediction tasks like Named Entity Recognition (NER). Demonstrations might not be robust for more structured prediction settings since these limited amounts of examples might not include much inductive bias. Also, using classifier-based fine-tuning demonstrations could be even more unreliable since there is no alignment between the demonstrations and the prediction space.

Concretely, we investigate the robustness of demonstration-based sequence labeling by design-

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ing pathological demonstrations: gradually ruling out the helpful information from the demonstrations. We surprisingly find that a working demonstration does not need to contain correct examples to observe improved performance. Furthermore, randomly replacing every token in the demonstration can still make a better few-shot learner even it is no longer a meaningful sentence and does not make any sense (Figure 1). This observation conflicts with some existing hypotheses (Gao et al., 2021; Lee et al., 2022) that models are learning meaningful knowledge from these demonstrations. We also find that the length of the pathological demonstration and the relevance of its random tokens drastically affect the performance. Empirical results on Name Regularity Bias (NRB) diagnose dataset (Ghaddar et al., 2021) shows that the demonstrations rarely help the performance when there is no easy patterns. Additionally, we show the pathological demonstrations can obtain similar or better performance on NLU tasks such as classification and natural language inference. In summary, our empirical results encourage the rethinking on how the demonstration helps the model obtain better few-shot capability and provides some insights.

2 Related Work

2.1 Demonstration-based Learning

Demonstrations are first introduced by the GPT series (Radford et al., 2019; Brown et al., 2020), where a few examples are sampled from training data and transformed with templates into appropriately-filled prompts. The existing demonstration-based learning research can be broadly divided into three categories based on the task reformulation and whether there is an update on the model parameters:

In-context Learning reformulates the task as a language modeling problem, and the model makes predictions by filling in the blank without using classifiers. In in-context learning, the model learns by only conditioning on the demonstration in a tuning-free way, while an enormous language model is often needed for this method (Brown et al., 2020; Zhao et al., 2021; Min et al., 2022a; Wei et al., 2022).

Prompt-based Fine-tuning also reformulates the task as a masked language modeling problem, and the demonstrations are incorporated as additional contexts (Gao et al., 2021). The model learns by fine-tuning on a small set of training data and moderately-sized PLMs are often used. Virtual demonstrations such as trainable embeddings (Liang et al., 2022) belong to this setting.

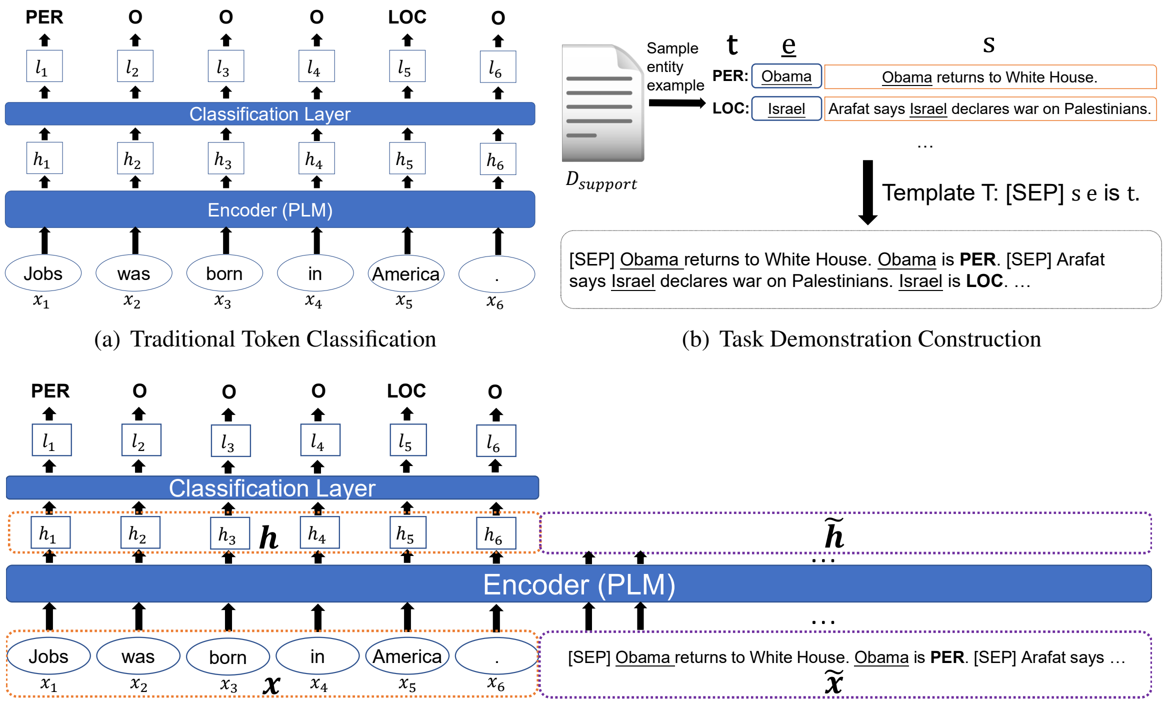
Classifier-based Fine-tuning requires no reformulation of the task and simply augments the original input with demonstrations (Lee et al., 2022). One advantage of this method is that it can benefit tasks such as sequence labeling when it is hard to be reformulated as (masked) language modeling.

Much work has been conducted to examine how to make a good sample selection (Liu et al., 2021a; Mishra et al., 2021) and ordering (Lu et al., 2021) as informative demonstrations are crucial for model performance. Our work focuses on the third demonstration-based learning method—classifier-based fine-tuning under the traditional token classification framework on sequence labeling tasks.

2.2 Analyses of Prompts and Demonstrations

With the recent prevalence of using prompts and demonstrations to stimulate the ability of PLMs under limited data scenarios (Schick and Schütze, 2021a,b; Liu et al., 2021b), a growing amount of works look at how prompting and demonstrations work. For instance, Webson and Pavlick (2021) studied different prompt templates and target words on NLI tasks mainly with the prompt-based fine-tuning method and found evidence that prompt-based models still perform well when irrelevant or even misleading prompts are used. Similarly, Min et al. (2022b) showed that in-context learning is not taking advantage of correct label mappings but more surface form in the demonstrations, like the distribution of the input text and the overall format of the sequence, while later work (Kim et al., 2022) argued the impact of correct mapping depends on different configurations. Logan IV et al. (2021) demonstrated fine-tuning language models on a few data can considerably reduce the need for prompt engineering, while Utama et al. (2021) showed that prompt-based fine-tuning improves the in-distribution performance while gradually increases models' reliance on surface heuristics. Garg et al. (2022) trained transformers to directly learn function classes provided in demonstrations and showed such learning is possible even under distribution shifts.

Different from them, we focus on the analysis of demonstration-based learning under the classifier-


PER
O
O
O
LOC
O
l_1 l_2 l_3 l_4 l_5 l_6
Classification Layer
h_1 h_2 h_3 h_4 h_5 h_6
Encoder (PLM)
Jobs was born in America .
x_1 x_2 x_3 x_4 x_5 x_6
Sample entity example
t e s
PER: Obama Obama returns to White House.
LOC: Israel Arafat says Israel declares war on Palestinians.
…
$D_{support}$
Template T: [SEP] s e is t.
[SEP] Obama returns to White House. Obama is PER. [SEP] Arafat says Israel declares war on Palestinians. Israel is LOC. …
$\boldsymbol{h}$
$\tilde{\boldsymbol{h}}$
…
[SEP] Obama returns to White House. Obama is PER. [SEP] Arafat says …
$\boldsymbol{x}$
$\tilde{\boldsymbol{x}}$

(a) Traditional Token Classification

(b) Task Demonstration Construction

(c) Demonstration-based Learning

Figure 2: An overview of (a) traditional token classification methods, (b) task demonstration construction process, and (c) demonstration-based learning for NER.

based fine-tuning framework on sequence labeling tasks where we do not reformulate the task into (masked) language model problems and therefore rule out the impact of target word selection. Furthermore, we create more effective and adversarial demonstrations consisting of only random tokens, showing that it is not only the in-context learning or prompt-based fine-tuning but also the traditional ways of utilizing PLMs that may trigger this counter-intuitive performance gain.

3 Problem Definition

This section focuses on demonstration-based learning under limited data scenario, by introducing concepts of limited data sequence labeling tasks in Section 3.1, as well as describing traditional token classification methods in Section 3.2 and demonstration-based learning in Section 3.3.

3.1 Limited Data Sequence Labeling Tasks

Given an input sentence $\mathbf{x} = [x_1, x_2, \cdots, x_n]$ composed of n tokens, the sequence labeling task is to predict a tag $y_i \in Y \cup \{O\}$ for each token x_i, where Y is a predefined set of tags such as {LOC, PER, ...} for Named Entity Recognition (NER) and {NP, VP, ...} for chunking, and O denotes outside a tagged span. Under limited data scenario, we only have K-shot support set $D_{support}$ for training which contains K examples for each tag type.

3.2 Traditional Token Classification Methods

As shown in Figure 2(a), traditional methods for sequence labeling use the encoders from PLMs such as BERT to encode the input $\mathbf{x} = [x_1, x_2, \cdots, x_n]$ to get contextualized representations for each token $\mathbf{h} = [h_1, h_2, \cdots, h_n]$, and then use a linear classifier or CRF layer to get the label estimation l_i for each token. The model is trained to minimize the cross entropy loss between l_i and y_i.

3.3 Demonstration-based Learning

Constructing Task Demonstration As shown in Figure 2(b), for each tag type $t^{(c)}$, we sample one tag example $e^{(c)}$, along with its original context $s^{(c)}$ from support set $D_{support}$. We use template T to convert them into type demonstration $d^{(c)} = T(s^{(c)}, e^{(c)}, t^{(c)})$, and then construct task demonstration $\tilde{\mathbf{x}}$ by concatenating all type demonstrations together:

$$\tilde{\mathbf{x}} = d^{(1)} \oplus d^{(2)} \oplus \cdots \oplus d^{(|Y|)}$$

Here $\oplus$ denotes the concatenation of input sequences. We further concatenate the original input

$\mathbf{x}$ with demonstration $\tilde{\mathbf{x}}$ to obtain demonstration-augmented input $[\mathbf{x}; \tilde{\mathbf{x}}]$. Prior work (Lee et al., 2022) have studied various example sampling strategies and templates to construct the demonstration. We adopt their `popular` strategy to choose $e^{(c)}$ that occurs most frequently among the corresponding examples and `context` template of "$s^{(c)}$. $e^{(c)}$ is $t^{(c)}$.", given their strong performances in Lee et al. (2022). Here, we refer the "$e^{(c)}$ is $t^{(c)}$." part in the template as labeling part of the demonstration.

Learning with Demonstration As shown in Figure 2(c), like traditional token classification methods, we feed the demonstration-augmented input $[\mathbf{x}; \tilde{\mathbf{x}}]$ into the encoder, and get the token representation $[\mathbf{h}; \tilde{\mathbf{h}}]$. We then feed $\mathbf{h}$ into the classification layer to get the label estimation l_i for each token in original input and train the model to minimize the cross entropy loss between l_i and y_i. Note that we use identical demonstrations during training and testing, which is crucial for demonstration-based learning to work (Lee et al., 2022).

4 Pathological Demonstrations

We refer to the demonstration constructed in Section 3.3 as **ST**andard (**ST**) demonstration. Suppose the model leverages the demonstrations in a human-analogous way and understands the meaning of them, there will be no more performance gains if we no longer provide correct example-label pairs or actual examples. To this end, we design three pathological demonstrations by gradually removing such intuitively helpful information from **ST** demonstrations:

1. **SW** (**S**tandard demonstration with **W**rong labels): Intuitively, the most helpful information in demonstrations is the correlation between provided examples and tag types, thus the first kind of pathological demonstrations provides wrong examples for each tag type on purpose.

2. **SN** (**S**tandard demonstration with **N**o label): Furthermore, the existence of examples or tags in labeling part of the demonstration might give away hints, so we remove the labeling part to create the second pathological demonstration that consists of only contexts from the support set.

3. **TR** (**T**otally **R**andom demonstration): Finally, we test a seemingly useless demonstration by using random token strings as demonstrations. Specifically, we replace every token in the demonstration **SN** with random tokens sampled from the vocabulary.

Mode	Template T	Example (for type PER)
ST	[SEP] s e is t.	[SEP] Obama returns to White House. Obama is PER.
SW	[SEP] s e is t'.	[SEP] Obama returns to White House. Obama is LOC.
SN	[SEP] s	[SEP] Obama returns to White House.
TR	[SEP] s'	[SEP] similar Requiem tracking Michelle seeds 15th
SR	[SEP] s''	[SEP] war House to on Arafat returns

Table 1: **Templates and examples for different modes of demonstrations**. Here, e denotes the entity example sampled for entity type t, and s denotes the sentence from the support set that contains entity e as type of t. s', s'' refer to the same sentence but with every token of it being replaced by random tokens sampled from whole vocabulary or *relevant* vocabulary (Section 5.4) respectively. All examples above are modified from the standard demonstration shown in Figure 2(b) and only part of them are displayed here. We show a list of real demonstrations we constructed and used in Appendix B.

We show templates and examples for these pathological demonstrations modified from standard demonstration for NER in Table 1.

5 Experiments

5.1 Few-Shot Datasets

Datasets We conduct experiments on two sequence labeling tasks: named entity recognition and chunking. For NER task, we use dataset **CoNLL03** (Tjong Kim Sang and De Meulder, 2003), and **OntoNotes 5.0** (Weischedel et al., 2013). Since we primarily focus on named entities, we omit the 7 value types in OntoNotes following Ma et al. (2021). In addition, we use **CoNLL00** (Tjong Kim Sang and Buchholz, 2000) for the chunking task. Since the number of some phrase types is very limited, we only consider 6 most frequent types (which are *NP, VP, PP, ADVP, SBAR* and *ADJP*, accounting for 99% of the labeled chunks).

Few-shot data sampling Different from sentence-level few-shot tasks, in sequence labeling, one sample for a class refers to a span in the sentence, and one sentence may contain multiple samples of different types. We follow the greedy sampling strategy proposed by Yang and Katiyar (2020) to sample K shots for each type in an increasing order with respect to their frequencies, the detailed algorithm can be found at Appendix C. The detailed dataset statistics are shown in Table 2.

Dataset	$\|Y\|$	L	$\|D_{support}\|$	$\|D_{test}\|$
CoNLL03	4	18	$8.0_{\pm1.1}$	3453
OntoNotes 5.0	11	21	$26.6_{\pm1.2}$	12217
CoNLL00	6	36	$8.6_{\pm0.8}$	2012

Table 2: **Data Statistics**. $|Y|$: # of entity types. L: average # of tokens in input sentence. $|D_{support}|$: average # of sentences in 5-shot support set over 5 different sub-samples. $|D_{test}|$: # of sentences in test set.

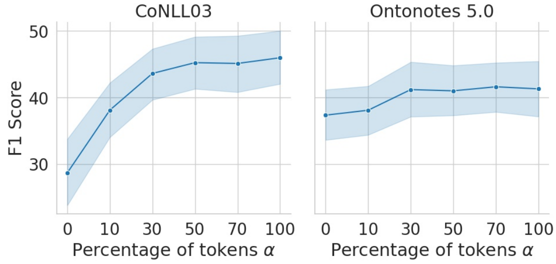


Figure 3: **Impact of demonstrations length.** Results for traditional token classification methods ($\alpha = 0$) and demonstration-based learning with pathological demonstration **SR** of different length, where α denotes the length is $\alpha\%$ of the original **SR** demonstration.

5.2 Implementation Details

We use `bert-base-cased` model from HuggingFace (Wolf et al., 2020) as our backbone for all the experiments and set the batch size and learning rate to 4 and 2e-5, respectively, following Lee et al. (2022). We use NVIDIA GeForce RTX 3080 Ti to conduct all experiments. For each variant, we run 50 epochs over 5 different sub-samples and 3 random seeds with early-stopping 20 and report its micro-F1 scores along with its recall and precision.

5.3 Results

We show the detailed results for demonstration-based learning with standard demonstrations and pathological demonstrations in Section 4, as well as traditional token classification methods with no demonstration in Table 3.

Demonstration is effective! Comparing results between no demonstration method (**NO**) and demonstration-based learning (**ST**), we found that demonstrations improve the few-shot performance significantly (e.g., from 28.71 to 46.25 on CoNLL03, and from 63.17 to 70.55 on CoNLL00). A closer look at reveals that the performance gains are mainly from a much higher recall for NER task, indicating demonstrations are mainly helping recognize more entities.

No need for labels? As shown in Table 3, there is no significant difference between the F1 scores of standard demonstration (**ST**) and its pathological variation **SW**. This suggests that a *working* demonstration even does not need to have the correct labels. Moreover, even if we remove the entire labeling part (often perceived as the most important factor for demonstrations), the pathological demonstration **SN** can still achieve as impressive results as **ST** demonstration. Our results are consistent with a recent work (Min et al., 2022b) that correct label mapping may not be needed for demonstrations to work, though we approach the robustness of demonstration based learning in a different classifier-based fine-tuning setting.

Random demonstration also works. Surprisingly, there is significant performance gain when using demonstration **TR** over **NO** (e.g., from 28.71 to 41.33 on CoNLL03, and from 63.17 to 69.28 on CoNLL00), though the gap between **TR** and **ST** demonstration still exists. Note that **TR** demonstration is no longer a real sentence and may not provide any meaningful or useful information.

5.4 Analysis

This section provides a deeper understanding of why and how demonstration-based learning works given the counter-intuitive results in Section 5.3.

Relevance of the tokens counts! Looking at the performance difference between demonstration **SN** and **TR**, we hypothesize that a key factor might be the random tokens' relevance to the input sentence. To test this, we construct a demonstration **SR** (**S**upport set sampled **R**andom demonstration) as shown in Table 1, by first creating a *relevant vocabulary* consisting of only tokens appear in the support set $D_{support}$, and then sampling tokens from this relevant vocabulary to replace tokens in demonstration. The result is shown in the last row of Table 3. We found that the performance of **SR** is superior to **TR** (45.99 v.s. 41.33 on CoNLL03) and comparable to **ST** demonstration (45.99 v.s. 46.25 on CoNLL03). This implies that the relevance of tokens of the demonstration is very essential to demonstration-based learning.

Length of demonstrations matters. Since there is not much semantic meaning included in the demonstration **SR**, another crucial difference between **SR** and **NO** is the length of random demon-

Mode	NER						Chunking		
	CoNLL03			OntoNotes 5.0			CoNLL00		
	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall
NO	28.71$_{\pm 10.31}$	39.96$_{\pm 11.25}$	22.68$_{\pm 9.09}$	37.37$_{\pm 7.58}$	33.80$_{\pm 6.79}$	41.92$_{\pm 8.85}$	63.17$_{\pm 4.22}$	59.28$_{\pm 5.05}$	67.72$_{\pm 3.51}$
ST	46.25$_{\pm 5.41}$	47.92$_{\pm 5.91}$	45.02$_{\pm 6.06}$	40.21$_{\pm 7.65}$	32.51$_{\pm 6.87}$	52.82$_{\pm 8.28}$	70.55$_{\pm 3.08}$	66.53$_{\pm 4.40}$	75.21$_{\pm 2.11}$
SW	46.23$_{\pm 5.63}$	47.91$_{\pm 6.04}$	45.01$_{\pm 6.29}$	39.94$_{\pm 7.38}$	32.27$_{\pm 6.59}$	52.50$_{\pm 8.11}$	70.75$_{\pm 3.05}$	66.80$_{\pm 4.39}$	75.33$_{\pm 2.14}$
SN	45.74$_{\pm 6.52}$	47.86$_{\pm 6.23}$	44.31$_{\pm 7.79}$	40.29$_{\pm 6.76}$	32.46$_{\pm 5.81}$	53.18$_{\pm 8.10}$	69.94$_{\pm 3.16}$	65.86$_{\pm 4.48}$	74.70$_{\pm 2.12}$
TR	41.33$_{\pm 7.36}$	45.41$_{\pm 7.37}$	38.22$_{\pm 7.65}$	39.71$_{\pm 7.56}$	32.28$_{\pm 6.56}$	51.63$_{\pm 8.75}$	69.28$_{\pm 2.78}$	64.75$_{\pm 3.85}$	74.57$_{\pm 1.66}$
SR	45.99$_{\pm 7.90}$	47.20$_{\pm 7.84}$	45.09$_{\pm 8.34}$	41.60$_{\pm 7.05}$	33.96$_{\pm 6.29}$	53.75$_{\pm 7.80}$	70.63$_{\pm 3.01}$	66.24$_{\pm 4.29}$	75.75$_{\pm 1.70}$

Table 3: Main results for traditional token classification method (**NO**) and demonstration-based learning with different modes of demonstrations under 5-shot scenario. We report mean and standard deviation of F1-score, precision, and recall over 15 runs (5 different sub-samples and 3 random seeds).

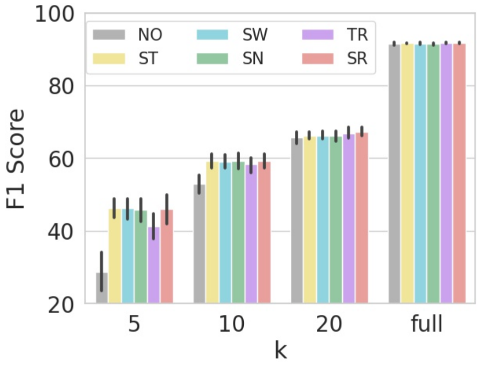


Figure 4: **Performance trends** under different level of data scarcity on CoNLL03 dataset.

Mode	F1	Precision	Recall
NO	52.08$_{\pm 7.02}$	56.52$_{\pm 6.46}$	48.42$_{\pm 7.59}$
ST	53.95$_{\pm 7.55}$	54.68$_{\pm 7.80}$	53.36$_{\pm 7.77}$
SW	53.60$_{\pm 7.41}$	54.33$_{\pm 7.86}$	53.00$_{\pm 7.36}$
SN	53.88$_{\pm 7.21}$	54.80$_{\pm 7.71}$	53.14$_{\pm 7.36}$
TR	53.57$_{\pm 6.55}$	55.01$_{\pm 6.92}$	52.25$_{\pm 6.46}$
SR	55.18$_{\pm 6.23}$	55.77$_{\pm 6.71}$	54.73$_{\pm 6.43}$

Table 4: Results for Roberta on CoNLL03 dataset under 5-shot scenario. We report mean and standard deviation of F1-score, precision, and recall over 15 runs (5 different sub-samples and 3 random seeds).

strations. Thus, we conducted ablation study by varying the length of demonstration **SR**. We evaluated the performance with demonstration consisting of $\alpha\%$ tokens of original **SR** demonstration. As shown in Figure 3, the performance of demonstration improves from 28.71 to 45.99 on CoNLL03 and from 37.37 to 41.60 on OntoNotes 5.0 with the longer length of α from 0 to 100; it saturates (achieving 98% of original **SR** demonstration's performance) at a relatively short length of 50% of the original length. This suggests that a fair number of tokens is needed for demonstration **SR** to be working, and it seems the length of demonstrations matters much more than their content. Our finding here is consistent with the finding in Xie et al. (2022).

The magic vanishes with more data. We further examine whether the performance gain of demonstration-based learning changes over different level of data scarcity, namely K-shots support set. We show results for the aforementioned (no) demonstrations under $K = 5, 10, 20$ shots and full data in Figure 4. The F1 score gain from demonstration is 17.54 (from 28.71 to 46.25) for 5-shot support set, 6.2 in the 10-shot setting, and negligible for the 20-shots support set and full data. Consistent with Lee et al. (2022); Gao et al. (2021), the performance gain (no matter standard or pathological) vanishes with more data. This indicates demonstrations have a strong boost on performance especially in extremely limited scenario, where there is no enough data for the model to fit well.

Similar findings on Roberta. To see whether this counter-intuitive finding holds on other PLMs as well, we experimented on Roberta with `roberta-base` model from HuggingFace and show the results in Tabel 4. Similar to the results on BERT, standard demonstration improves the performance by 1.87 F1-score while pathological demonstrations with no intuitively meaningful information work as well. It implies that the cause behind this counter-intuitive finding is not only specific to BERT, but may aslo be prevalent with other PLMs.

6 Understanding the Demonstrations

We take a closer look at the surprising performance of (pathological) demonstrations to examine whether such strong performance has any connections with spurious patterns or dataset bias, which the deep learning models are constantly being accused of leveraging (Wang et al., 2021). As a case study, we use a carefully designed testbed NRB (Ghaddar et al., 2021) to diagnose Name Regularity Bias in the NER models learned with demonstrations (Section 6.1). We also conduct experiments on the more popular way of utilizing demonstrations with prompts in Section 6.2 to show the effectiveness of pathological demonstrations.

6.1 Name Regularity Bias

Name Regularity Bias (Ghaddar et al., 2021; Lin et al., 2020) in NER occurs when a model relies on a signal from the entity name to make predictions and disregards evidence from the local context. For example, given the input sentence "*Obama is located in far southwestern Fukui Prefecture.*", modern NER models may wrongly predict the entity *Obama* as *PER*, while the context clearly signals it is a *LOC*. Therefore, Ghaddar et al. (2021) carefully designed a testbed utilizing the Wikipedia disambiguation page to diagnose Name Regularity Bias of NER models. The NRB dataset contains examples whose labels can be easily inferred from the local context but hard to be tagged by a popular NER system. The WTS dataset is a domain control set that contains the same query terms covered by NRB, but can be correctly labeled by both the popular NER tagger and local context-only tagger.

6.1.1 Results

We use both the NRB and WTS datasets to evaluate the model trained with different modes of demonstrations on CoNLL03 under 5,10,20-shots support set and full data. The result is shown in Figure 5. As we can see, demonstration-based learning on the control set WTS consistently brings impressive performance gains under all low-resource settings (e.g. from 27.00 to 68.07 with 5-shots support set, and from 69.76 to 82.57 with 20-shots support set). On challenging dataset NRB, it only shows a performance gain from 15.82 to 29.44 with 5-shots support set, with no performance gain with 10-shots support set and even decreased F1 scores with the 20-shots support set. This suggests that demonstration-based learning leverages the name regularity bias to recognize entities rather than the context information.

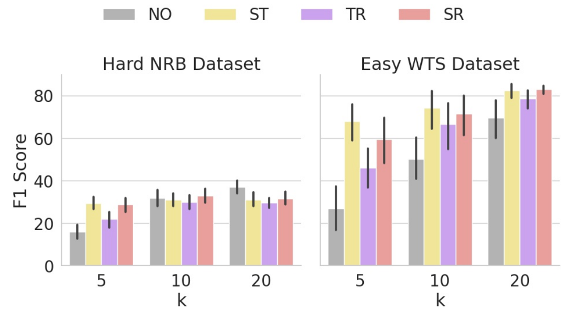


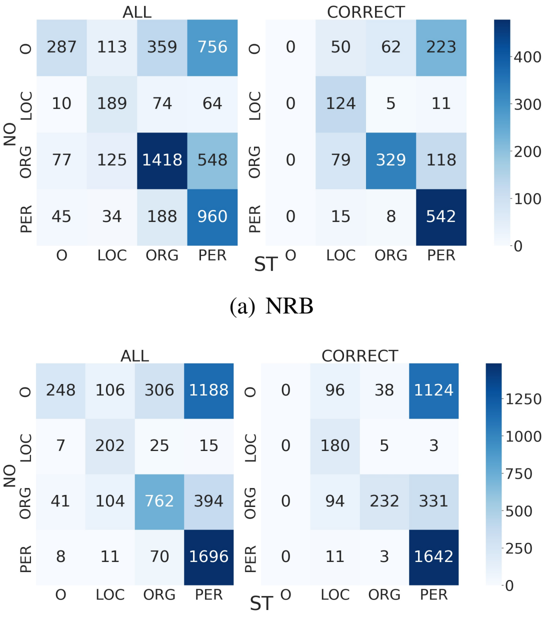
Figure 5: **Performance trend on NRB and WTS dataset**, with the model trained on the CoNLL03 dataset. Though demonstration-based learning consistently brings performance gain on the WTS dataset (right), it helps less or hurt performance on the NRB dataset (left).

6.1.2 Analysis

Demonstrations bring no robust improvements To have a better understanding on how demonstrations affect the performance, we show the detailed prediction flips for all entities after adding **ST** demonstrations to **NO** in Figure 6, where each cell shows the number of predictions that flip from the original prediction (row) to the new prediction with **ST** demonstrations (column), while the diagonal represents the number of predictions that remain unchanged. The left figure contains the overall number of such prediction flips and the right figure contains the number of such prediction flips that are correct. As we can see, though there is a similar pattern of prediction flip on both NRB and WTS, the correctness of these prediction flips are different. For the challenging dataset NRB, the prediction flip with the highest number, namely O → PER and ORG → PER, have a relatively low correct ratio of only $29\%(223/756)$ and $22\%(118/548)$, compared with $95\%(1124/1188)$ and $84\%(331/394)$ respectively on WTS. The second row in Table 5 shows an example of the wrong prediction flip for token "Clinton" from *O* to *PER*, while the true label should be *LOC*. Demonstrations can better recognize entities, but can not distinguish well among the entity types and misguide the model to make more false positive predictions on NRB. This further supports that demonstrations are not making robust improvements and simply leverage the name regularity bias.

Dataset	Input	Confidence with mode NO				Confidence with mode ST			
		O	LOC	ORG	PER	O	LOC	ORG	PER
NRB	A post office operated at Clinton from 1856 to 1859.	**0.88**	0.05	0.04	0.03	**1.0**	0.0	0.0	0.0
	A post office operated at Clinton from 1856 to 1859.	**0.37**	0.18	0.13	0.32	0.16	0.33	0.13	**0.38**
WTS	It was confirmed that Clinton had signed to	0.32	0.10	0.15	**0.43**	0.04	0.01	0.01	**0.94**
	Clinton has eight CDs and two DVDs available .	**0.67**	0.05	0.09	0.19	0.20	0.06	0.06	**0.68**

Table 5: **Examples from NRB and WTS dataset.** The token being predicted in the input is highlighted in yellow. The confidence score is **bold** for the final prediction (a.k.a the highest), and underlined for the true label.



(a) NRB

(b) WTS

Figure 6: Number of prediction flips for entities from mode **NO** (row) to **ST** (column). Left shows all prediction flips for entities while right shows the only ones that are correct with mode **ST**.

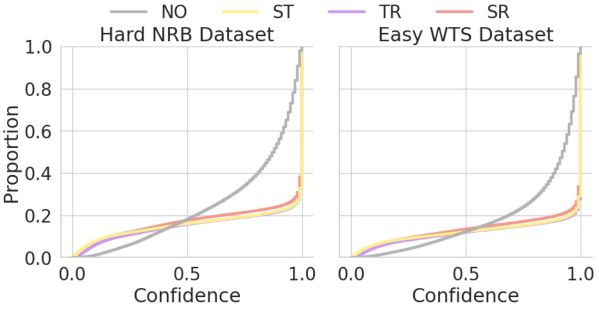


Figure 7: **Empirical cumulative distribution function of model's confidence on its final prediction.**

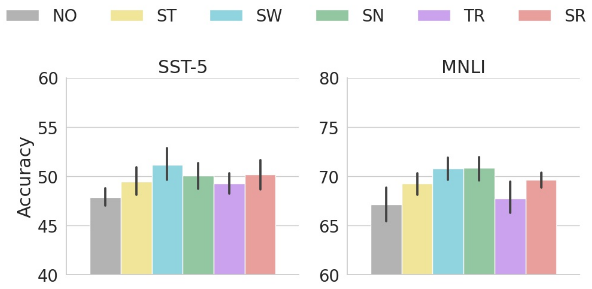


Figure 8: **Results of using pathological demonstrations with LM-BFF on SST-5 and MNLI.** Here we report averaged accuracy over 5 random seeds.

Demonstrations increase the confidence of model predictions To take a closer look at how these prediction flips work, we show the detailed confidence score (*a.k.a* the probability) for models' predictions with some illustrative examples in Table 5. Notably, in the first and third row, the confidence for token "post" to be *O* and "Clinton" to be *PER* increase from 0.88 to 1.0 and 0.43 to 0.94 respectively, therefore we hypothesize demonstrations increase the confidence of model's final prediction. We show empirical cumulative distribution function (ecdf) of the model's confidence for the final prediction with different modes of demonstrations on both NRB and WTS benchmarks in Figure 7. We found that, with demonstrations (either standard or random), the model tends to be more confident.

6.2 Demonstrations with prompt-tuning

Our construction of pathological demonstrations can be easily generalized to other types of demonstration-based learning, such as the prompt-based fine-tuning used in LM-BFF (Gao et al., 2021). Following their settings, we conduct experiments with `roberta-large` model on single-sentence task SST-5 (Socher et al., 2013) and sentence-pair task MNLI (Williams et al., 2018) with 16-shots support set, as shown in Figure 8. We found that the performance of pathological demonstrations is competitive with standard demonstrations, consistent with our findings on sequence labeling tasks with classifier-based fine-tuning.

7 Discussion and Conclusion

In this paper, we study the robustness of demonstration-based learning by designing pathological demonstrations. We found that, replacing demonstrations with random tokens still makes the model a better few-shot learner; the length of random token strings and the sampling space for random tokens are the main factors affecting the performance; and demonstrations increase the confidence of model predictions on captured superficial patterns such as the name regularity bias. Below we discuss the broader impacts of our findings.

Our findings imply that natural language is not sufficiently understood by the PLMs when being utilized together with demonstrations, since random token strings also lead to similar strong performances. Similar to our work, recent studies (Ri and Tsuruoka, 2022; Chiang and Lee, 2022) also found models pretrained on random token strings with a nesting dependency structure still provide transferable knowledge to downstream fine-tuning, suggesting the insufficient utilization of natural language during pretraining. We urge future work on demonstration based learning to think twice about their model performance gains by designing more robustness tests and ablation studies.

Our work also calls for a better design of demonstrations that are free of spurious patterns, as existing demonstrations are less effective while there is no spurious patterns to leverage (see Section 6.1). Future work should not only optimize the performances of demonstration based methods on the validation set, but also pay attention to whether these models suffer from spurious patterns and how to increase their generalization abilities.

Limitations

This work is subject to several limitations. First, we primarily look at sequence labeling tasks in this work, and have not applied similar techniques for other tasks such as text classification. Second, we followed Lee et al. (2022) to use the widely used `bert-base-cased` as our backbone for most of our experiments. A thorough examination of other language models such as T5 is needed, which we leave as future work. Finally, the present work focuses on understanding the robustness of demonstration-based learning, and we have not developed any practical guidelines on how to use our findings to design more effective demonstrations.

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A Additional Experimental Details

We use `bert-base-cased` model from HuggingFace (Wolf et al., 2020) as our backbone and use NVIDIA GeForce RTX 3080 Ti to conduct all experiments. The model have roughly 110M parameters and takes 1 hour for each mode of demonstration on average to train under 5-shot scenario.

B Example Demonstrations

We show a list of real demonstrations we constructed and used in the experiments for CoNLL03 and CoNLL00 in Table 6 and Table 7.

C Sampling Algorithm

We follow the greedy sampling strategy proposed by Yang and Katiyar (2020) to sample K shots for each tag in an increasing order with respect to their frequencies, the detailed algorithm is shown in Algorithm 1.

Algorithm 1: Greedy sampling

```
Require: # of shot $K$, labeled set $\mathbf{X}$ with tag set $\mathcal{C}$
Sort classes in $\mathcal{C}$ based on their freq. in $\mathbf{X}$
$S \leftarrow \phi$ //Initialize the support set
$\{\text{Count}_i \leftarrow 0\}$ //Initialize counts of entity classes in $\mathcal{S}$
while $i < |\mathcal{C}|$ do
    while $\text{Count}_i < K$ do
        Sample $(\mathbf{x}, \mathbf{y}) \in \mathbf{X}$ s.t. $\mathcal{C}_i \in \mathbf{y}$, w/o replacement
        $S \leftarrow S \cup \{(\mathbf{x}, \mathbf{y})\}$
        Update $\{\text{Count}_j\}$ $\forall \mathcal{C}_j \in \mathbf{y}$
    end while
end while
return $\mathcal{S}$
```

ST	[SEP] 9/16 - Luo Yigang (China) beat Jason Wong (Malaysia) 15-5 15-6 China is LOC . [SEP] Fox said the British government wanted an end to the alleged harassment of its nationals at Dhaka airport by customs officials . British is MISC . [SEP] One dealer said positive stances from Merrill Lynch and SBC Warburg were the key factors behind the gains . Merrill Lynch is ORG . [SEP] +2 D.A. Weibring through 12 D.A. Weibring is PER .
SW	[SEP] 9/16 - Luo Yigang (China) beat Jason Wong (Malaysia) 15-5 15-6 China is MISC . [SEP] Fox said the British government wanted an end to the alleged harassment of its nationals at Dhaka airport by customs officials . British is ORG . [SEP] One dealer said positive stances from Merrill Lynch and SBC Warburg were the key factors behind the gains . Merrill Lynch is PER . [SEP] +2 D.A. Weibring through 12 D.A. Weibring is LOC .
SN	[SEP] 9/16 - Luo Yigang (China) beat Jason Wong (Malaysia) 15-5 15-6 [SEP] Fox said the British government wanted an end to the alleged harassment of its nationals at Dhaka airport by customs officials . [SEP] One dealer said positive stances from Merrill Lynch and SBC Warburg were the key factors behind the gains . [SEP] +2 D.A. Weibring through 12
TR	[SEP] ##llan costs similar Requiem tracking Michelle seeds 15th HM influenced ##OH ##inia canyon visited USB punished ##ter hadn mom ##BA ##rrow ##hetto ##loss idea [SEP] carriages ##uk Mellon inconsistent archaeologists Server quartet Low Downs ##izations Bears ##titis again falsely sprawling Dennis hey plural exam goalkeeper kingdom Argentine [SEP] befriended ##ndi accept 1926 symbolic Colonel reviewer sketch rabbi Tampa ##orra tour Jul minorities ##iary closing Beta Sunday Jai counts quasi ##uminous [SEP] ambitious Funk Got ##orm types Another Elements growled ##aris evaluation resulted
SR	[SEP] Everton Merrill gains ##s One Moldova Ho beauty British qualifier S Lynch Dhaka through said 1995 Merrill ##ull beauty opening 12 working 9 . [SEP] Ta qualifier of 9 Russian through harassment Ho Dhaka up England airport its key ##burg republic ##man ##nch called Malaysia wounds) [SEP] by ##ron China ##burg dealer (Malaysia said Glenn up 9 in customs ##tars officials at + factors Jason Tale ##nife ##s [SEP] ##tars taken up behind husband 12 end Yi dealer S government

Table 6: **Example demonstrations for different modes constructed with method in Section 4**. The dataset used here is CoNLL03 for NER task. Example demonstrations for **TR** and **SR** are shown as a string of tokens.

ST	[SEP] Joe Mack , a district manager for Cormack Enterprises Inc. , a Burger King operator in Omaha , Neb. , says discounting is so prevalent that “ we have to serve 15 % to 20 % more customers ” to keep sales level . so prevalent is ADJP . [SEP] As surely as a seesaw tilts , falling interest rates force up the price of previously issued bonds . up is ADVP . [SEP] Pamela Sutherland , executive director of the Illinois Planned Parenthood Council , says she and her allies are “ cautiously optimistic ” they can defeat it if it comes to a floor vote . it is NP . [SEP] An investment group led by Chicago ’s Pritzker family recently lowered a $ 3.35 billion bid for American Medical International , Beverly Hills , Calif. , because of the threat of the legislation . of is PP . [SEP] Joe Mack , a district manager for Cormack Enterprises Inc. , a Burger King operator in Omaha , Neb. , says discounting is so prevalent that “ we have to serve 15 % to 20 % more customers ” to keep sales level . that is SBAR . [SEP] Joe Mack , a district manager for Cormack Enterprises Inc. , a Burger King operator in Omaha , Neb. , says discounting is so prevalent that “ we have to serve 15 % to 20 % more customers ” to keep sales level . says is VP .
SW	[SEP] Joe Mack , a district manager for Cormack Enterprises Inc. , a Burger King operator in Omaha , Neb. , says discounting is so prevalent that “ we have to serve 15 % to 20 % more customers ” to keep sales level . so prevalent is ADVP . [SEP] As surely as a seesaw tilts , falling interest rates force up the price of previously issued bonds . up is NP . [SEP] Pamela Sutherland , executive director of the Illinois Planned Parenthood Council , says she and her allies are “ cautiously optimistic ” they can defeat it if it comes to a floor vote . it is PP . [SEP] An investment group led by Chicago ’s Pritzker family recently lowered a $ 3.35 billion bid for American Medical International , Beverly Hills , Calif. , because of the threat of the legislation . of is SBAR . [SEP] Joe Mack , a district manager for Cormack Enterprises Inc. , a Burger King operator in Omaha , Neb. , says discounting is so prevalent that “ we have to serve 15 % to 20 % more customers ” to keep sales level . that is VP . [SEP] Joe Mack , a district manager for Cormack Enterprises Inc. , a Burger King operator in Omaha , Neb. , says discounting is so prevalent that “ we have to serve 15 % to 20 % more customers ” to keep sales level . says is ADJP .
SN	[SEP] Joe Mack , a district manager for Cormack Enterprises Inc. , a Burger King operator in Omaha , Neb. , says discounting is so prevalent that “ we have to serve 15 % to 20 % more customers ” to keep sales level . [SEP] As surely as a seesaw tilts , falling interest rates force up the price of previously issued bonds . [SEP] Pamela Sutherland , executive director of the Illinois Planned Parenthood Council , says she and her allies are “ cautiously optimistic ” they can defeat it if it comes to a floor vote . [SEP] An investment group led by Chicago ’s Pritzker family recently lowered a $ 3.35 billion bid for American Medical International , Beverly Hills , Calif. , because of the threat of the legislation . [SEP] Joe Mack , a district manager for Cormack Enterprises Inc. , a Burger King operator in Omaha , Neb. , says discounting is so prevalent that “ we have to serve 15 % to 20 % more customers ” to keep sales level . [SEP] Joe Mack , a district manager for Cormack Enterprises Inc. , a Burger King operator in Omaha , Neb. , says discounting is so prevalent that “ we have to serve 15 % to 20 % more customers ” to keep sales level .
TR	[SEP] ##llan costs similar Requiem tracking Michelle seeds 15th HM influenced ##OH ##inia canyon visited USB punished ##ter hadn mom ##BA ##rrow ##hetto ##loss idea carriages ##uk Mellon inconsistent archaeologists Server quartet Low Downs ##izations Bears ##titis again falsely sprawling Dennis hey plural exam goalkeeper kingdom Argentine befriended ##ndi accept 1926 symbolic Colonel [SEP] reviewer sketch rabbi Tampa ##orra tour Jul minorities ##iary closing Beta Sunday Jai counts quasi ##uminous ambitious Funk Got ##orm types [SEP] Another Elements growled ##aris evaluation resulted announcement Upon complications Brighton ##umble ##mat compromise grinned Fritz conversations cavalry aids conflicts Kung Bayern Soundtrack ##ny remarried ##pta indicates cautious ##gis arch LP Event clip ##ake lobbying Majority Nam select ##khar neighbourhood [SEP] Preliminary Barclay ##it dialogue html ##ce ##bul Zimbabwe combines ##uch capacity challenged Burgess Stations freestyle vulnerable unbeaten Bordeaux Hyderabad Hearing Zeus Romania ##ulate Dead Zhang fullback ##kley cruisers Burke Specialist ##uy Yuri Trains Cedar Strait rested und Ultra duel attempts Campo [SEP] step landing losses ##bones emotions ripe ##sad Williamson ##MO Tour ##DS catalogue ##mbs Pietro Text ##ão Ada British chalk biologist stating reigned tastes favorites 1839 seduce ##track Chilean Arab Johnston ##human creative ##dox their spotlight subsidies pounding ashore eroded Chart ##bull worldwide battled inclusion Verona ##bull BP computers losses nurses analogue 1870 [SEP] specialised bony differing I scarce ##EN ##oring reached peak Lea ##stones ##press ##hall ##tic march tuning attacked portion Dietrich Leaving Romani purchased mosques ##physical stimulate rejected stages ##mart Constance manipulate remote Maya redesigned hazardous seeded usage Scholars follower Endowment Zionist Otto speeding ##nch accusations wrath inconsistent Madras Isles classics likewise cousin 360
SR	[SEP] take ##if ’ ##age ##front % we Mack post Hills firm ##age not American ##up are P s Medical prevalent to rates preferring ’ industry says look takes w not allies that defeat e ##ed fur investment said line ##ck entrepreneur are 5 ##ed ##rma prevalent Peter fined Hills Medical director International [SEP] 18 made , preferring sales line family News comes word the executive bid escaped T un From and months wherever ##eb [SEP] ##o . family cents have Ka Mr bid or to Beverly director ##ed if capitalism ##sty prison Enterprises Pamela sentenced is dollar level w capital bet 35 talk capitalism Burger The News % Enterprises floor director Con take an [SEP] entirely that stock false poorly R ##nn a have many P line one ##rent level 3 so do look one so only falling Pa sound comes district sales Mack 20 prices industry word sales this cloak ‘ cloak ##rent months that [SEP] Mack force ##s Medical gone recently ##if ##rma From ##ck ##urn capital are ##hem 3 Illinois director ##hem vote bonds more escaped group capital other because capital word year level R sound 5 ##if T optimistic ##ck if An other other sales interest Peter operator rates Cal From ##har poorly take rates [SEP] talk says ##rma Sutherland Peter Enterprises death president bonds An ##isms filing tilt by ##if months un line pleaded 15 a 15 do bid for ##print ##aw ##rier . said The R threat threat 43 surely be Inc sales bonds talk are so death gone News an discount t guilty ##rent dollar

Table 7: **Example demonstrations for different modes constructed with method in Section 4**. The dataset used here is CoNLL00 for chunking task. Example demonstrations for **TR** and **SR** are shown as a string of tokens.