Robustness of Demonstration-based Learning
Under Limited Data Scenario

Hongxin Zhang\textsuperscript{1}, Yanzhe Zhang\textsuperscript{2}, Ruiyi Zhang\textsuperscript{3}, Diyi Yang\textsuperscript{4}

\textsuperscript{1}Shanghai Jiao Tong University, \textsuperscript{2}Georgia Institute of Technology
\textsuperscript{3}Adobe Research, \textsuperscript{4}Stanford University

\texttt{icefox@sjtu.edu.cn, z_yanzhe@gatech.edu, ruizhang@adobe.com, 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 \url{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 \textit{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.

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-
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) diagnosis 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-
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 \( x = [x_1, x_2, \ldots, x_n] \) 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 \( x = [x_1, x_2, \ldots, x_n] \) to get contextualized representations for each token \( h = [h_1, h_2, \ldots, h_n] \), 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 \( \tilde{x} \) by concatenating all type demonstrations together:

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

Here \( \oplus \) denotes the concatenation of input sequences. We further concatenate the original input
x with demonstration \( \tilde{x} \) to obtain demonstration-augmented input \([x; \tilde{x}]\). 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 \([x; \tilde{x}]\) into the encoder, and get the token representation \([h; \tilde{h}]\). We then feed \( h \) 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 STandard (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** (Standard demonstration with Wrong 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** (Standard demonstration with No 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** (Totally Random demonstration): Finally, we test a seemingly useless demonstration by using random token strings as demonstrations.

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

Specifically, we replace every token in the demonstration SN with random tokens sampled from the vocabulary.

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.
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 (Support set sampled Random 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 demonstration.
The performance gain of demonstration-based learning changes over different levels 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 Table 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 also be prevalent with other PLMs.

**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).

| Mode | F1 | Precision | Recall |
|------|----|-----------|--------|
| NO   | 28.71±10.31 | 39.96±11.25 | 22.68±9.09 |
| ST   | 46.25±5.51  | 47.92±5.91  | 45.02±6.06  |
| SW   | 46.23±5.63  | 47.91±6.04  | 45.01±6.29  |
| SN   | 45.74±5.62  | 47.86±6.23  | 44.31±7.79  |
| TR   | 41.33±3.76  | 45.41±3.77  | 38.22±7.65  |
| SR   | 45.99±7.90  | 47.20±7.84  | 45.09±8.34  |

**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).

| Mode | F1 | Precision | Recall |
|------|----|-----------|--------|
| NO   | 52.08±7.02 | 56.52±6.46 | 48.42±7.59 |
| ST   | 53.95±7.55 | 54.68±7.80 | 53.36±7.77 |
| SW   | 53.60±7.41 | 54.33±7.86 | 53.00±7.36 |
| SN   | 53.88±7.21 | 54.80±7.71 | 53.14±7.36 |
| TR   | 53.57±6.55 | 55.01±6.92 | 52.28±6.46 |
| SR   | 55.18±6.23 | 55.77±6.71 | 54.73±6.43 |
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.

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. 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.
A post office operated at Clinton from 1856 to 1859.

It was confirmed that Clinton had signed to Clinton has eight CDs and two DVDs available.

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.

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.

Acknowledgements

The authors would like to thank reviewers for their helpful insights and feedback. This work is funded in part by grants from Adobe and Amazon.

References

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Yoss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual.

Cheng-Han Chiang and Hung-yi Lee. 2022. On the transferability of pre-trained language models: A study from artificial datasets. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 36, pages 10518–10525.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Tianyu Gao, Adam Fisch, and Danqi Chen. 2021. Making pre-trained language models better few-shot learners. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 3816–3830, Online. Association for Computational Linguistics.

Shivam Garg, Dimitris Tsipras, Percy Liang, and Gregory Valiant. 2022. What can transformers learn in-context? a case study of simple function classes.

Abbas Ghaddar, Philippe Langlais, Ahmad Rashid, and Mehdi Rezagholizadeh. 2021. Context-aware Adversarial Training for Name Regularity Bias in Named Entity Recognition. Transactions of the Association for Computational Linguistics, 9:586–604.

Jiaxin Huang, Chunyuan Li, Krishan Subudhi, Damien Jose, Shobana Balakrishnan, Weizhu Chen, Baolin Peng, Jianfeng Gao, and Jiawei Han. 2021. Few-shot named entity recognition: An empirical baseline.
study. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 10408–10423, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Junyean Kim, Hyuhung Joon Kim, Hyunsoo Cho, Hwiyeol Jo, Sang-Woo Lee, Sang goo Lee, Kang Min Yoo, and Taeuk Kim. 2022. Ground-truth labels matter: A deeper look into input-label demonstrations.

Brenden Lake, Ruslan Salakhutdinov, and Joshua Tenenbaum. 2015. Human-level concept learning through probabilistic program induction. Science, 350:1332–1338.

Dong-Ho Lee, Akshen Kadakia, Kangmin Tan, Mahak Agarwal, Xinyu Feng, Takashi Shibuya, Ryosuke Mitani, Toshiyuki Sekiya, Jay Pujara, and Xiang Ren. 2022. Good examples make a faster learner: Simple demonstration-based learning for low-resource NER. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 2687–2700, Dublin, Ireland. Association for Computational Linguistics.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7871–7880, Online. Association for Computational Linguistics.

Xiaozhuan Liang, Ningyu Zhang, Siyuan Cheng, Zhen Bi, Zhenru Zhang, Chuanqi Tan, Songfang Huang, Fei Huang, and Huajun Chen. 2022. Contrastive demonstration tuning for pre-trained language models. arXiv preprint arXiv:2204.04392.

Hongyu Lin, Yaojie Lu, Jialong Tang, Xianpei Han, Le Sun, Zhicheng Wei, and Nicholas Jing Yuan. 2020. A rigorous study on named entity recognition: Can fine-tuning pretrained model lead to the promised land? In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 7291–7300, Online. Association for Computational Linguistics.

Jiachang Liu, Dinghan Shen, Yizhe Zhang, Bill Dolan, Lawrence Carin, and Weizhu Chen. 2021a. What makes good in-context examples for gpt-3? arXiv preprint arXiv:2101.06804.

Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. 2021b. Pretrain, prompt, and predict: A systematic survey of prompting methods in natural language processing. ArXiv preprint, abs/2107.13586.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized BERT pretraining approach. CoRR, abs/1907.11692.

Robert L Logan IV, Ivana Balažević, Eric Wallace, Fabio Petroni, Sameer Singh, and Sebastian Riedel. 2021. Cutting down on prompts and parameters: Simple few-shot learning with language models. arXiv preprint arXiv:2106.13353.

Yao Lu, Max Bartolo, Alastair Moore, Sebastian Riedel, and Pontus Stenetorp. 2021. Fantastically ordered prompts and where to find them: Overcoming few-shot prompt order sensitivity. arXiv preprint arXiv:2104.08786.

Ruotian Ma, Xin Zhou, Tao Gui, Yiding Tan, Qi Zhang, and Xuanjing Huang. 2021. Template-free prompt tuning for few-shot NER. CoRR, abs/2109.13532.

Sewon Min, Mike Lewis, Hannaneh Hajishirzi, and Luke Zettlemoyer. 2022a. Noisy channel language model prompting for few-shot text classification. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 5316–5330, Dublin, Ireland. Association for Computational Linguistics.

Sewon Min, Xinxi Lyu, Ari Holtzman, Mikkel Artetxe, Mike Lewis, Hannaneh Hajishirzi, and Luke Zettlemoyer. 2022b. Rethinking the role of demonstrations: What makes in-context learning work? arXiv preprint arXiv:2202.12837.

Swaroop Misra, Daniel Khashabi, Chitta Baral, and Hannaneh Hajishirzi. 2021. Cross-task generalization via natural language crowdsourcing instructions. arXiv preprint arXiv:2104.08773.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. OpenAI blog, 1(8):9.

Ryokan Ri and Yoshimasa Tsuruoka. 2022. Pretraining with artificial language: Studying transferable knowledge in language models. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 7302–7315, Dublin, Ireland. Association for Computational Linguistics.

Timo Schick and Hinrich Schütze. 2021a. Exploiting cloze-questions for few-shot text classification and natural language inference. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 255–269, Online. Association for Computational Linguistics.

Timo Schick and Hinrich Schütze. 2021b. It’s not just size that matters: Small language models are also few-shot learners. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 2339–2352, Online. Association for Computational Linguistics.
Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Ng, and Christopher Potts. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pages 1631–1642, Seattle, Washington, USA. Association for Computational Linguistics.

Erik F. Tjong Kim Sang and Sabine Buchholz. 2000. Introduction to the CoNLL-2000 shared task chunking. In *Fourth Conference on Computational Natural Language Learning and the Second Learning Language in Logic Workshop*.

Erik F. Tjong Kim Sang and Fien De Meulder. 2003. Introduction to the CoNLL-2003 shared task: Language-independent named entity recognition. In *Proceedings of the Seventh Conference on Natural Language Learning at HLT-NAACL 2003*, pages 142–147.

Prasetya Utama, Nafise Sadat Moosavi, Victor Sanh, and Iryna Gurevych. 2021. Avoiding inference heuristics in few-shot prompt-based finetuning. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 9063–9074, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Xuezhi Wang, Haohan Wang, and Diyi Yang. 2021. Measure and improve robustness in nlp models: A survey. *arXiv preprint arXiv:2112.08313*.

Albert Webson and Ellie Pavlick. 2021. Do prompt-based models really understand the meaning of their prompts? *arXiv preprint arXiv:2109.01247*.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Ed Chi, Quoc Le, and Denny Zhou. 2022. Chain of thought prompting elicits reasoning in large language models. *arXiv preprint arXiv:2201.11903*.

Ralph Weischedel, Martha Palmer, Mitchell Marcus, Eduard Hovy, Sameer Pradhan, Lance Ramshaw, Nianwen Xue, Ann Taylor, Jeff Kaufman, Michelle Franchini, et al. 2013. Ontonotes release 5.0 ldc2013t19. *Linguistic Data Consortium, Philadelphia, PA*, 23.

Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. A broad-coverage challenge corpus for sentence understanding through inference. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 1112–1122, New Orleans, Louisiana. Association for Computational Linguistics.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online. Association for Computational Linguistics.

Qizhe Xie, Zihang Dai, Eduard Hovy, Thang Luong, and Quoc Le. 2020. Unsupervised data augmentation for consistency training. In *Advances in Neural Information Processing Systems*, volume 33, pages 6256–6268. Curran Associates, Inc.

Sang Michael Xie, Aditi Raghunathan, Percy Liang, and Tengyu Ma. 2022. An explanation of in-context learning as implicit bayesian inference. In *International Conference on Learning Representations*.

Yi Yang and Arzoo Katiyar. 2020. Simple and effective few-shot named entity recognition with structured nearest neighbor learning. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 6365–6375, Online. Association for Computational Linguistics.

Zihao Zhao, Eric Wallace, Shi Feng, Dan Klein, and Sameer Singh. 2021. Calibrate before use: Improving few-shot performance of language models. In *International Conference on Machine Learning*, pages 12697–12706. PMLR.
A Additional Experimental Details

We use the \texttt{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.

\hspace{1cm}

\begin{algorithm}[H]
\caption{Greedy sampling}
\begin{algorithmic}
\Require \# of shot $K$, labeled set $X$ with tag set $\mathcal{C}$
\State Sort classes in $\mathcal{C}$ based on their freq. in $X$
\State $S \leftarrow \emptyset$ //Initialize the support set
\State \{$\text{Count}_i \leftarrow 0$\} //Initialize counts of entity classes in $S$
\While{$i < |\mathcal{C}|$}
\While{\text{Count}_i < K}
\State Sample $(x, y) \in X$ s.t. $C_i \in y$, w/o replacement
\State $S \leftarrow S \cup \{(x, y)\}$
\EndWhile
\State Update \{$\text{Count}_j \}$ $\forall C_j \in y$
\EndWhile
\State \Return $S$
\end{algorithmic}
\end{algorithm}

1780
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.
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 ADVP.

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. 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. [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 ADVP.

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. 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. [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 ADVP.

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.

1782