Self-Generated In-Context Learning: Leveraging Auto-regressive Language Models as a Demonstration Generator

Hyuhng Joon Kim†, Hyunsoo Cho†, Junyeob Kim†, Taeuk Kim‡, Kang Min Yoo†§¶, Sang-goo Lee†
†Seoul National University, ‡Hanyang University, §NAVER AI Lab, ¶NAVER CLOVA
{heyjoonkim, johyunsoo, junyl16, sglee}@europa.snu.ac.kr
kimtaeuk@hanyang.ac.kr
kangmin.yoo@navercorp.com

Abstract

Large-scale pre-trained language models (PLMs) are well-known for being capable of solving a task simply by conditioning a few input-label pairs dubbed demonstrations on a prompt without being explicitly tuned for the desired downstream task. Such a process (i.e., in-context learning), however, naturally leads to high reliance on the demonstrations which are usually selected from external datasets. In this paper, we propose self-generated in-context learning (SG-ICL), which generates demonstrations for in-context learning from PLM itself to minimize the reliance on the external demonstration. We conduct experiments on four different text classification tasks and show SG-ICL significantly outperforms zero-shot learning and is generally worth approximately 0.6 gold training samples. Moreover, our generated demonstrations show more consistent performance with low variance compared to randomly selected demonstrations from the training dataset.

1 Introduction

The scale of pre-trained language models (PLMs) is ever-growing as they tend to deliver more meaningful results with larger models and have reached the scale of hundreds of billions. However, transferring such large-scale PLMs with the traditional method i.e., fine-tuning, is problematic as it entails an immense cost to train and store parameters for an individual task. Numerous branches of work have been proposed to circumvent such issues, such as Adapters (Houlsby et al., 2019), LoRA (Hu et al., 2021), and in-context learning (ICL) (Brown et al., 2020).

Among others, ICL is in the limelight as it derives answers only from the internal knowledge of PLMs without any parameter updates. Specifically, ICL learns to solve a task simply by conditioning a few input-label pairs dubbed demonstrations on a prompt, which serves to give contexts regarding the downstream task during the inference phase, allowing PLMs to solve the tasks better. The working principle of ICL intuitively leads to high reliance on the demonstrations, and performance deeply varies depending on the assortment of the demonstrations.

Many lines of work tackled the issue of ICL’s high reliance on the demonstration. For instance, Lu et al. (2021) shown in-context learning suffers from the order sensitivity of the demonstrations. Zhao et al. (2021) introduces a contextual calibration procedure to reduce the variance across different choices of demonstrations. Rubin et al. (2021) suggests demonstration selection by retrieving in-context samples. Notably, Liu et al. (2022) showed that selecting a demonstration that has a high correlation with the test input can improve performance.

Motivated by previous research considering the limits of ICL’s working process, we tried to solve the following research question:

1. Can we eliminate the dependency on the training dataset by generating demonstrations?
2. If so, how can we create demonstrations with high input-demonstration correlation?

To this end, we propose a novel method termed self-generated in-context learning (SG-ICL) which generates demonstrations by leveraging the superiority of PLMs generative abilities (Adiwardana et al., 2020; Brown et al., 2020; Shwartz et al., 2020; Ye et al., 2022). To the best of our knowledge, this is the first study to utilize PLMs to create demonstrations for ICL. SG-ICL consists of two operation steps: the self-generation step and the inference step. In the self-generation step, we generate demonstrations for each class in the downstream task by conditioning on the current test input and class information with a simple manually designed template. By giving conditions about the current input, PLM can generate demonstrations with a high input-demonstration correlation which is more befitted for ICL. Then, the inference step performs ICL with generated demonstrations.
Figure 1: Overall process of SG-ICL. Texts in yellow are manually designed prompts for generation and the texts in red are expected class for generated demonstration. Demonstrations (colored in blue) are generated in the self-generation step and are reused for in-context learning in the inference step. Texts in green are manually designed inference prompts.

from the previous step which eliminates the requirement for training data or manual selection from training data.

We evaluate our method in four different natural language understanding (NLU) tasks, including sentiment classification and natural language inference. Through extensive experiments, we show that SG-ICL significantly outperforms zero-shot learning methods and is generally worth approximately 0.6 gold training samples. Moreover, our generated demonstrations show more stable performance with low variance compared to randomly selected demonstrations from training dataset.

2 Method

2.1 Few-shot Learning

Given a PLM $P$, our objective is to solve a classification task $D_{test} = (X_{test}, Y_{test})$. A natural language template $T(\cdot)$ is provided, containing additional information about the downstream task. A limited number of training data $D_{train} = (X_{train}, Y_{train})$ is available as demonstration. Inference input is generated by concatenating $k$ training samples and the test input with the template. Additionally, we define a verbalizer $V(\cdot)$ (Schick and Schütze, 2020) which maps each class $y_i \in Y$ to a pre-defined token. The final prediction is made by selecting the class with the highest probability for the mapped token:

$$p(y_i | x_{test}^i) = P(V(y_i)) | T(x_{train}^1, y_{train}^1), ..., T(x_{train}^k, y_{train}^k), T(x_{test}^i))$$ (1)

Zero-shot learning is a special case of few-shot learning where the number of training data $k = 0$.

2.2 Self-generated In-context Learning

SG-ICL can be divided into two steps: the self-generation step and the inference step. In the first step, we generate demonstrations conditioned on the test input and a specific class. This way we can generate demonstrations highly correlated with the test input. Details about the generation methods will be further discussed in Section 3.3. In the second step, we use the self-generated samples as a demonstration for in-context learning. The overall process of SG-ICL is visualized in Figure 1.

Self-generation Step In the self-generation step, we generate in-context sample $s_i$. Specifically, generation template $G(\cdot)$ is defined, which takes the test instance $x_{test}^i \in X_{test}$ and a class token $V(y_i)$ as an input. The PLM $P$ takes the generation input $G(x_{test}^i, V(y_i))$ and generates in-context sample $s_i$.

For single-sentence tasks (e.g., SST-2 and SST-5), the generation input can be defined as $G(x_{test}^i, V(y_i))$. The generated in-context sample $x_{gen}^i$ would be pairs of $(s_i, y_i)$. In sentence-pair tasks (e.g., RTE and CB) consisting of sentence-pair inputs $x_{i,1}, x_{i,2}$, the generation input can be
defined as $G(x_{i,1}, x_{i,2}, V(y_i))$. In this case, generated in-context sample $x_{i}^{\text{gen}}$ would be a set of $(x_{i,1}, s_{i}, y_{i})$.

**Inference Step** In the inference step, we use the generated samples as the demonstration for in-context learning. In detail, we take each generated samples $x_{i}^{\text{gen}}$ and convert them using the inference template $T(\cdot)$. The inference input is generated by concatenating all $k$ generated samples and the test instance. The prediction is made in the same way as few-shot learning:

$$p(y_i \mid x_i^{\text{test}}) = P(V(y_i)) \mid T(x_{i}^{\text{gen}}, y_{i}^{\text{gen}}), \ldots, T(x_{i}^{\text{gen}}, y_{i}^{\text{gen}}), T(x_i^{\text{test}}) \tag{2}$$

3 Experiments

3.1 Experimental Setup

**Datasets and Metrics** We report results on four text classification datasets: sentiment classification with SST-2 (Socher et al., 2013) and SST-5 (Socher et al., 2013), natural language inference with CB (De Marneffe et al., 2019) and RTE (Dagan et al., 2005). We report accuracy for all tasks. All reported results are averaged over 5 different random seeds. See Table 2 in Appendix A for details about the datasets.

**Baselines** We compare SG-ICL with zero-shot learning and few-shot learning with 8 in-context samples. 2 different inference templates were used: minimal and manual. For inference templates and verbalizers, see Table 3 in Appendix B.

**Models** The main experiments were done with GPT-J (6B) (Wang, 2021), one of the largest publicly available auto-regressive models. We used the implementation and the pre-trained weights from Huggingface Transformers library (Wolf et al., 2019).

3.2 Main results

Figure 2 is our main experimental results with the settings stipulated above. We compare SG-ICL with zero/few-shot learning with the same number of in-context samples. We observed that SG-ICL performs significantly better than zero-shot learning, consistent across all four text classification tasks. This result is significant since both zero-shot learning and SG-ICL does not have any access to training data, but SG-ICL was able to gain improvements by using self-generated in-context samples.

Additionally, we can observe that the performance with SG-ICL is stable with very low variance. As in-context learning is highly dependent on the choice of the demonstration, its performance fluctuations are not negligible. SG-ICL alleviates this downside by generating an input conditioned sample highly correlated with the input instance and provides stable performance.

3.3 Why condition on the input?

In this section, we show the effect of conditioning on the input instance during the generation process. To do so, we conduct a simple experiment comparing two types of generation methods: (1) conditioning only on the class and (2) conditioning on both the class and the input instance. Previous work (Liu et al., 2022) has shown that in-context samples semantically-similar to the input instance are more likely to serve as a better in-context sample, improving performance. Based on previous research, we conduct an experiment to see whether...
| Method               | SST-2 | SST-5 |
|---------------------|-------|-------|
| class conditioned   | 0.0689| 0.0735|
| input-class conditioned | **0.3051** | **0.3098** |

Table 1: Cosine similarity of the input instance and the generated demonstration. Inputs with similar sentence embedding have higher cosine similarity. Generating samples conditioned on both the input and the class shows higher cosine similarity.

Figure 3: Results comparing two different generation methods alongside zero/few-shot in-context learning. Generating samples conditioned additionally on the input instance provides more performance gain.

conditioning on the input instance has a significant impact on the performance gain. We first calculate the correlation between the generated sample and the input instance. We use the sentence embedding from Reimers and Gurevych (2019) and calculate the cosine similarity between the two instance. Table 1 shows the results on SST-2 and SST-5. We can observe that samples generated conditioned on the input instance shows a higher correlation with the input instance.

To verify the correlation between the similarity and the downstream task performance, we report the downstream task performance of the two generation methods. The results are shown in Figure 3. Regardless of the generation method, making use of the generated demonstrations provides performance gain. Additionally, we can observe in-context samples conditioned additionally on input instance performs better, aligning with the results in Table 1.

3.4 How many in-context samples does self-generation worth?

We first analyze the significance of self-generated in-context samples in SG-ICL. To do so, we show few-shot learning performances with a varying number of in-context samples from 1 to 8 and compare it with SG-ICL. Figure 4 shows the results on two tasks: SST-2, SST-5. The results show that using 8 self-generated in-context samples can outperform few-shot learning with at most 5 gold training samples consistently. Experiments show one self-generated in-context sample worth about 0.6 gold training sample.

4 Conclusion & Future Work

In this paper, we propose self-generated in-context learning (SG-ICL), generating in-context samples and reusing them as demonstrations. We were able to generate quality demonstrations, eliminating the need for training data during in-context learning. Our experiments on four text classification datasets show that SG-ICL can provide significant improvements in performance without the use of any training data. Moreover, SG-ICL show more stable performance with low variance compared to randomly selected demonstrations from training dataset.

As the quality of the generated samples is highly dependent on the generation abilities of the PLM, applying SG-ICL to larger PLMs would likely show significant improvements and is left as future work. Despite the positive results in natural language understanding tasks, applying SG-ICL to other tasks is not fully explored. Future work could...
include applying SG-ICL in various task domains.

**Acknowledgements**

This work was supported by SNU-Naver Hyper-scale AI Center.

**References**

Daniel Adiwardana, Minh-Thang Luong, David R So, Jamie Hall, Noah Fiedel, Romal Thoppilan, Zi Yang, Apoorv Kulshreshtha, Gaurav Nemane, Yifeng Lu, et al. 2020. Towards a human-like open-domain chatbot. *arXiv preprint arXiv:2001.09977*.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901.

Ido Dagan, Oren Glickman, and Bernardo Magnini. 2005. The pascal recognising textual entailment challenge. In *Machine Learning Challenges Workshop*, pages 177–190. Springer.

Marie-Catherine De Marneffe, Mandy Simons, and Judith Tonhauser. 2019. The commitmentbank: Investigating projection in naturally occurring discourse. In *proceedings of Sinn und Bedeutung*, volume 23, pages 107–124.

Geoffrey Hinton, Oriol Vinyals, Jeff Dean, et al. 2015. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*, 2(7).

Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin de Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. 2019. Parameter-efficient transfer learning for nlp. In *ICML*.

Edward Hu, Yelong Shen, Phil Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Lu Wang, and Weizhu Chen. 2021. Lora: Low-rank adaptation of large language models.

Jiacheng Liu, Dinghan Shen, Yizhe Zhang, Bill Dolan, Lawrence Carin, and Weizhu Chen. 2022. What makes good in-context examples for GPT-3? In *Proceedings of Deep Learning Inside Out (DeeLIO 2022): The 3rd Workshop on Knowledge Extraction and Integration for Deep Learning Architectures*, pages 100–114, Dublin, Ireland and Online. Association for Computational Linguistics.

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*.

Nils Reimers and Iryna Gurevych. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics.

Ohad Rubin, Jonathan Herzig, and Jonathan Berant. 2021. Learning to retrieve prompts for in-context learning. *arXiv preprint arXiv:2112.08633*.

Timo Schick and Hinrich Schütze. 2020. Exploiting cloze questions for few shot text classification and natural language inference. *arXiv preprint arXiv:2001.07676*.

Vered Shwartz, Peter West, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. 2020. Unsupervised commonsense question answering with self-talk. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4615–4629, Online. Association for Computational Linguistics.

Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D Manning, Andrew Y 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.

Ben Wang. 2021. Mesh-Transformer-JAX: Model-Parallel Implementation of Transformer Language Model with JAX. https://github.com/kingoflolz/mesh-transformer-jax.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funkowicz, et al. 2019. Huggingface’s transformers: State-of-the-art natural language processing. *arXiv preprint arXiv:1910.03771*.

Jiacheng Ye, Jiahui Gao, Qintong Li, Hang Xu, Jiangtao Feng, Zhiyong Wu, Tao Yu, and Lingpeng Kong. 2022. Zerogen: Efficient zero-shot learning via dataset generation. *arXiv preprint arXiv:2202.07922*.

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 Dataset Details**

Table 2 shows detailed statistics of the datasets used in the main experiment.

**B Templates for Generation and Inference**

Table 4 and Table 3 shows details of the prompts and verbalizers used for inference and generation, respectively.
| Dataset | # of Train Set | # of Validation Set | # of Classes |
|---------|----------------|---------------------|--------------|
| SST-2   | 67,349         | 872                 | 2            |
| SST-5   | 8,544          | 2,210               | 5            |
| RTE     | 2,490          | 277                 | 2            |
| CB      | 250            | 57                  | 3            |

Table 2: Datasets used for experiments.
| Task        | Inference Template                                                                 | Verbalizer     |
|------------|-----------------------------------------------------------------------------------|----------------|
| Minimal    | a fast, funny, highly enjoyable movie.                                             | positive/-     |
| SST-2      | **Review**: a fast, funny, highly enjoyable movie.                                | positive / negative |
|            | **Sentiment**: positive                                                            |                |
| SST-5      | **Review**: it’s worth taking the kids to.                                         | terrible / bad/okay / good / great |
|            | **Sentiment**: great                                                               |                |
| RTE        | **Premise**: Dana Reeve, the widow of the actor Christopher Reeve, has died of lung cancer at age 44, according to the Christopher Reeve Foundation. | true / false   |
|            | **Hypothesis**: Christopher Reeve had an accident.                                |                |
| CB         | **Premise**: It was a complex language. Not written down but handed down. One might say it was peeled down.  | yes / no / neither |
|            | **Hypothesis**: the language was peeled down                                        |                |
|            | Yes, No, or Neither? yes                                                            |                |

Table 3: Templates and verbalizers for inference. Texts in red are manually designed prompts and texts in blue are expected output for prediction. The rightmost column shows tokens mapped with each class.

| Task        | Generation Template                                                                 |
|------------|-------------------------------------------------------------------------------------|
| SST-2      | Generate a review: a fast, funny, highly enjoyable movie.                           |
|            | Generate a "negative" review:                                                      |
| SST-5      | Generate a review: it’s worth taking the kids to.                                   |
|            | Generate a "negative" review:                                                      |
| RTE        | **Premise**: Dana Reeve, the widow of the actor Christopher Reeve, has died of lung cancer at age 44, according to the Christopher Reeve Foundation. | Generate a Hypothesis: Christopher Reeve had an accident.  |
|            | Generate a "true" Hypothesis:                                                      |
| CB         | **Premise**: It was a complex language. Not written down but handed down. One might say it was peeled down.  | Generate a Hypothesis: the language was peeled down |
|            | Generate a "neither" Hypothesis:                                                   |

Table 4: Templates for self-generating in-context samples. Texts in red are manually designed prompts for generation and texts in blue are tokens representing the expected class.