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Improving In-Context Few-Shot Learning via Self-Supervised Training

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Abstract

Self-supervised pretraining has made few-shot learning possible for many NLP tasks. But the pretraining objectives are not typically adapted specifically for in-context few-shot learning. In this paper, we propose to use self-supervision in an intermediate training stage between pretraining and downstream few-shot usage with the goal to teach the model to perform in-context few shot learning. We propose and evaluate four self-supervised objectives on two benchmarks. We find that the intermediate self-supervision stage produces models that outperform strong baselines. Ablation study shows that several factors affect the downstream performance, such as the amount of training data and the diversity of the self-supervised objectives. Human-annotated cross-task supervision and self-supervision are complementary. Qualitative analysis suggests that the self-supervised-trained models are better at following task requirements.

1 Introduction

In-context few-shot learning seeks to solve unseen tasks at inference time by conditioning on a few training examples. In particular, in this case we are interested in methods that forgo any weight updates (Brown et al., 2020). Prior work has been focused on improving inference time algorithms (e.g., rescoring generated outputs (Zhao et al., 2021), selecting (Liu et al., 2021) and ordering (Lu et al., 2021) the given few-shot examples) and incorporating extra resources (e.g., fine-tuning models on human-annotated datasets (Mishra et al., 2021; Ye et al., 2021; Wei et al., 2022)).

We hypothesise that a different way to improve in-context few-shot learning is through designing self-supervised objectives that more closely resemble the format of tasks that the model will be asked to perform. To do so, we cast the self-supervised training as an intermediate training stage between language model pretraining and downstream few-shot evaluation. In particular, we construct training datasets based on the self-supervised objectives following similar formats used in the downstream tasks, fine-tune pretrained language model checkpoints on the training datasets, and then evaluate the models on benchmarks.

In experiments, we consider four self-supervised objectives, including masked word prediction and classification tasks related to next sentence prediction (Devlin et al., 2019). We evaluate models on two benchmarks (13 tasks in total): SuperGLUE (Wang et al., 2019) and Natural-Instructions (Mishra et al., 2021). SuperGLUE focuses on discriminative tasks, and Natural-Instructions is a set of generative tasks.

Empirically, we experiment with pretrained language models of two sizes: 125 million parameters and 1.3 billion parameters. We show that in our best setting, the 1.3 billion parameters model trained by the self-supervision performs better than the initial pretrained language models and two strong baselines on average.

Further analysis reveals that (1) the effectiveness of the self-supervision depends on the amount of training data, but the benefit of adding more data is diminishing; (2) the improvements brought by the self-supervision are in part due to the semantic similarity between the training and evaluation tasks; (3) adding more self-supervised objectives may not help model performance because adding them does not contribute to the diversity of the self-supervised tasks; (4) choosing similar task templates for both self-supervised and downstream tasks plays a vital role in improving model performance; (5) self-supervised tasks and human-annotated datasets are complementary; (6) generation examples show that compared to the initial pretrained language models, self-supervised-trained models are better at following the task instructions.

*Work done during an internship at Meta AI.
2 Related Work

In-Context Few-Shot Learning. Brown et al. (2020) discover that large pretrained language models can solve unseen tasks at inference time. Recent work has improved the in-context few-shot performance by rescoring generated outputs (Zhao et al., 2021), selecting (Liu et al., 2021) and ordering (Lu et al., 2021) the given few-shot examples. Other work studies pretrained language models’ cross-task generalization abilities for in-context few-shot or zero-shot learning using human-annotated datasets (Ye et al., 2021; Wei et al., 2022; Sanh et al., 2022; Min et al., 2021; Xu et al., 2022) via instructions (Weller et al., 2020; Efrat and Levy, 2020; Mishra et al., 2021; Ouyang et al., 2022) and retrieved examples (Hu et al., 2022; Lin et al., 2022). Our work differs in that we focus on self-supervised training.

Fine-Tuning for Few-Shot Learning. Pretrained language models for few-shot learning typically follows the “pretrain then fine-tune” paradigm (Howard and Ruder, 2018; Radford et al., 2018; Devlin et al., 2019, inter alia), where recent work has focused on designing templates for few-shot fine-tuning (Reynolds and McDonell, 2021; Schick and Schütze, 2021a,c,b; Le Scao and Rush, 2021; Tam et al., 2021; Gao et al., 2021; Sørensen et al., 2022), and optimizing soft prompts (Li and Liang, 2021; Qin and Eisner, 2021; Lester et al., 2021; Gu et al., 2021; Zhang et al., 2022). Other work focuses on unifying task formats to maximize the benefits of human annotations, including question answering (Zhong et al., 2021), textual entailment (Yin et al., 2019, 2020; Wang et al., 2021a), and many other tasks (McCann et al., 2018; Keskar et al., 2019; Raffel et al., 2020; Bragg et al., 2021). In contrast, our focus is on in-context few-shot learning, without fine-tuning models on downstream task examples.

Pretraining for Few-Shot Learning. Several papers have adapted various resources for pretraining models to enhance their performances on few-shot learning, such as pretraining on hypertext (Aghajanyan et al., 2021b), question-infused pretraining (Jia et al., 2021), and self-training (Du et al., 2021; Vu et al., 2021; Wang et al., 2021b). Pretraining approaches have targeted specific tasks, such as task-oriented dialog (Mi et al., 2021), intent detection (Zhang et al., 2021), and data-to-text generation (Chen et al., 2020). Our work differs as we use plain text as opposed to (naturally-occurring) human-annotated resources. Relatedly, Bansal et al. (2020) used self-supervised meta-learning for few-shot text classification rather than in-context few-shot learning.

Intermediate Fine-Tuning. Since our approach involves an extra training stage between pretraining and downstream evaluation, it is also related to prior work that uses multi-stage fine-tuning on human-annotated datasets for generic tasks (Phang et al., 2018; Pruksachatkun et al., 2020; Chang and Lu, 2021; Aghajanyan et al., 2021a; Poth et al., 2021) and text classification (Zhang and Zhang, 2021). Relevant work also studies intermediate fine-tuning using cross-lingual supervision (Phang et al., 2020; Moghe et al., 2021). Rubino and Sumita (2020) use an intermediate self-supervised training stage for machine translation quality estimation.

3 Method

We describe four self-supervised training objectives that will be used to train models before downstream evaluations.

We begin by defining the example and the instance used during our self-supervised training. An example is an input-output pair. To differentiate the input and the output, we append special tokens “Input:” and “Output:” to the beginning of input text and output text respectively where the two texts are also separated by the ⟨newline⟩ token (see Figure 1 for examples).

An instance is a linearized string formed by several examples from the same task (e.g., see Figure 2). As we encode the text using causal attention, the examples closer to the beginning of input sequences can be seen as task demonstrations, resulting in efficient computation.

When constructing the training examples, we pick three or more consecutive sentences (depending on the minimum sequence length we enforce on the sentences) and then apply task-specific rules to automatically create training data. To form a training instance, we randomly select examples from the same task until reaching the maximum sequence length (i.e., 2048). During training, we compute a cross-entropy loss on tokens in the output texts.

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1 We chose this special symbol because we always start the self-supervised training from a pretrained language model checkpoint.
Natural language processing is a subfield of computer science concerned with the interactions between computers and human language. The goal is a computer capable of "understanding" the contents of documents.

Next Sentence Generation
Input: Natural language processing is a subfield of computer science concerned with the interactions between computers and human language. Output: The goal is a computer capable of "understanding" the contents of documents.

Last Phrase Prediction (Generation)
Input: Natural language processing is a subfield of computer science concerned with the interactions between computers and human language. Question: The goal is a computer capable of "understanding"? Output: False

Last Phrase Prediction (Classification)
Input: Natural language processing is a subfield of computer science concerned with the interactions between computers and human language. Question: The goal is a computer capable of "understanding"? Answer: The goal is a computer capable of "understanding".

Figure 1: Examples of our self-supervised training tasks. Each example is an input-output pair constructed from the raw text.

Figure 2: An example of a training instance. Each instance is formed by several training examples. During training, we use left-to-right language models and compute a cross-entropy loss on the output texts (indicated by the red color in the shown example). We note that when computing the loss on the second example, the first example can be seen as task demonstrations. For brevity, we show part of the input and output texts.

We describe details of the self-supervised tasks in the following subsections.

3.1 Next Sentence Generation

In light of the strong performance of language models on in-context few-shot learning (Brown et al., 2020), we incorporate the language modeling as one of our self-supervised tasks, which we call “next sentence generation” (NSG). NSG asks the model to generate the next sentence given previous sentences as context. When building data for this task, we use the last sentence as output and the rest of the sentences as input.

3.2 Masked Word Prediction

The second task we consider is based on masked word prediction (MWP) which is commonly used in pretraining generic text encoders (Devlin et al., 2019; Liu et al., 2019). The task asks the model to fill in the missing information based on the surrounding context. Specifically, MWP randomly replaces words in input sentences with a special symbol and requires models to recover the masked words in the input. For this task, we create input text by randomly replacing 1–20 words in the input text with a special token2 and use the masked out words as the output text.

3.3 Last Phrase Prediction

Inspired by the LAMBADA dataset (Paperno et al., 2016), a question answering dataset which asks models to predict the last word in a sentence given several sentences of context, we create a “last phrase prediction” (LPP) task, which requires predicting the last phrase in a sentence. To solve this task, models need to draw relevant information from the context and the learned knowledge during pretraining. We cast LPP as either a generation task or a classification task. The latter variant of LPP is a binary classification task that labels if the given answer is the correct phrase. To facilitate a unified format of these two tasks, we append a special token “Question:” to the beginning of the last sentence and replace the last phrase with a question mark. For the classification LPP, we separate the given answer and the previous context and sentences with a special token “Answer:”.

More specifically, we identify the last phrase of a sentence based on a set of function words (see appendix A.5 for the list of function words). If there are multiple function words in a sentence, we pick the last one. Then we treat the text segment starting from the function word as the last phrase.

2We randomly select the special token from the following list: ___ ⟨⟨⟩⟩, @@@, @, ((), $ $$ % %, ###, ***, and +++.

3We ensure that the last sentence in raw text for this task always has at least one valid function word and the function
Natural language processing is a subfield of computer science concerned with the interactions between computers and human language. The goal is a computer capable of understanding the contents of documents.

Figure 3: Example illustrating the construction of training instances for our classification task. There are four input types, and each training instance has two or three types. As the shown instance has the following two types: "original sentences" and "different documents", it comprises examples from two different documents. The instance resembles the next sentence prediction task, encouraging models to compare topical similarities between the two examples.

When selecting negative answers, we randomly choose from the phrases extracted from the same function words (to make the negative answers more challenging).

3.4 Classification

Similar to the next sentence prediction task (Devlin et al., 2019) and the sentence ordering prediction task (Jernite et al., 2017; Chen et al., 2019) for pretraining language representations, we create a classification task (CL) for our self-supervised training. As shown in Figure 3, for this task, we consider four types of input: original sentences, shuffled sentences, sentences from a different document, and sentences from multiple documents. In particular, for original sentences, we directly use text from original human-written documents. For shuffled sentences, we randomly shuffle all the input sentences. For sentences from multiple documents, we randomly replace 50% of the input sentences with sentences from another document. We also ensure that the selected sentences (from both the input and another document) are consecutive in their original documents. For sentences from different documents, we replace the input sentences with sentences from another document. See Figure 3 for an example of each type of input.

When constructing a training instance, we randomly pick one or two additional input types and combine them with the original sentences to form a binary or three-way classification task. We also randomly assign label strings to input types in each instance to ensure that models follow the information given by earlier examples when making predictions.

The classification task is different from the other self-supervised tasks described in earlier subsec-

4 Experiment

4.1 Training Setup

For the pretrained language model checkpoints, we use the 125 million parameters (125M) and the 1.3 billion parameters (1.3B) dense model from Artetxe et al. (2021). These pretrained models have shown results comparable to GPT3 across various tasks.

For self-supervised training, we use a subset of documents from the RoBERTa training corpus (Liu et al., 2019) that contains four domains: BOOKCORPUS plus Wikipedia, CC-NEWS, OpenWebText, and STORIES. Specifically, we randomly sample 100k documents from each domain except STORIES where we only sample 10k documents as the documents there are much longer than the others. The final training data contains approximately 1 million instances with 250k training instances per task.4 For the 125M model, we train for 10 epochs, which takes roughly 1 day on a V100 GPU. For the 1.3B model, we train for 5 epochs, which takes roughly 3 days on 2 V100 GPUs.

4.2 Evaluation Setup

The instance and example during evaluation shares similar definition as those in Sec. 3 except that each evaluation instance has only one example from test splits and it is placed at the last position in the instance. The other examples in the instance

4The average numbers of example per instance for each data source are: 6.9 for BOOKCORPUS plus Wikipedia, 5.3 for CC-NEWS, 3.5 for OpenWebText, and 7.2 for STORIES.
We evaluate the models on two benchmarks: SuperGLUE and Natural-Instructions. SuperGLUE is a set of tasks focusing on natural language understanding. We use BoolQ (BQ; Clark et al., 2019), CB (De Marneffe et al., 2019), COPA (CA; Roemmele et al., 2011), MultiRC (MC; Khashabi et al., 2018), and RTE (RE; Giampiccolo et al., 2007; Bentivogli et al., 2009; Dagan et al., 2006; Bar Haim et al., 2006). We report results for the official development sets. The task demonstrations are examples randomly selected from the training sets. We report mean and standard deviations of five runs with different random seeds. Following GPT3, we use a ranking based approach when evaluating the models (i.e., pick the best label based on language modeling perplexities).

Natural-Instructions. Natural-Instructions evaluates models’ cross-task generalization abilities where all the tasks are generation tasks. It splits the tasks into two groups for training and evaluation. We use the same task split and evaluate models on the following task categories: question generation (QG), answer generation (AG), minimal modification (MM), and verification (VF). Each task category has two tasks. Following the few-shot setting used in Mishra et al. (2021), we evaluate models using 100 examples per task, use greedy decoding, and report ROUGE-L (Lin, 2004) scores per task category. For task demonstrations, we use the positive examples in the instructions in

- SuperGLUE. As our self-supervised tasks are formatted as input-output pairs, we change the task-specific templates for SuperGLUE to make them more similar to our self-supervised tasks. For example, as shown in Table 1, we make MultiRC similar to the classification LLP. More details of the template changes are in appendix A.6.

For both benchmarks, we also report an averaged performance for each model. For SuperGLUE, the average performance is computed based on the means of task performances. When a task has two metrics, we take the average of the two as the task performance.

More details on the dataset statistics and metrics for each task for both benchmarks are in appendix A.2.

Baselines. We consider four baselines: (1) directly evaluating pretrained language models on the benchmarks (LM); (2) performing additional language modeling training on the subset of the original data that is used for constructing the self-supervised tasks (ExtraLM). We use ExtraLM to approximately measure the contribution of additional computation; (3) fine-tuning on training sets for the tasks outside the evaluation sets (CrossTask). We use CrossTask to estimate the performances of cross-task supervision from human-annotated datasets; and (4) fine-tuning on training sets for the tasks in the evaluation sets (SameTask). SameTask serves as an oracle baseline estimating the approximated upperbound performances of cross-task supervision.

Since SuperGLUE does not have an official split for the CrossTask setting, we split the datasets into two groups according to the task category and report the CrossTask results based on “CrossTask (QA→NLI)” and “CrossTask (NLI→QA).” As we alter the task templates, we report results for evaluating the pretrained language model check-
We report the results for SuperGLUE and Natural-Instructions when varying the number of examples used for self-supervised training.

5 Analysis

5.1 Effect of Amount of Data

In Figure 4, we report model performances for the 1.3B model on SuperGLUE and Natural-Instructions with 1%, 10%, 20%, 50%, and 200% points using the new templates (NewTemplate) to study the effect of new templates.

4.3 Results

We report the results for SuperGLUE and Natural-Instructions in Table 2 and Table 3. Our findings are as follows:

1. Our proposed self-supervised training achieves the best performance on average for both benchmarks.

2. ExtraLM and NewTemplate show similar performances as the pretrained language model checkpoints, suggesting that the improvements from our self-supervised training is unlikely to come from the additional training on the data and the task template changes.

3. Compared to the pretrained language model checkpoints, CrossTask shows worse performances on both benchmarks, which is likely due to the differences between training tasks and evaluation tasks.
Table 6: Average results when adding denoising autoencoding and gap sentence prediction to the self-supervised training. ALL: use all of the self-supervision described in Sec. 3.

| Model | SuperGLUE Results | Natural-Instructions Results |
|-------|-------------------|----------------------------|
|       | ALL               | ALL+MoreTask              |
| 125M  | 51.0              | 50.9                      |
| 1.3B  | 55.6              | 55.6                      |

Table 7: Average model performance comparing whether we assign random labels to the self-supervised tasks.

| LM    | Correct Label | Random Label |
|-------|---------------|--------------|
|       | SuperGLUE Results | Natural-Instructions Results |
|       | 125M | 51.0 | 38.2 |
|       | 1.3B | 55.6 | 42.5 |
|       | 125M | 30.0 | 19.1 |
|       | 1.3B | 45.5 | 31.5 |

Table 8: Average results for SuperGLUE when using different task templates. MS=model size.

| Model | MS | GPT3 Template | Our Template |
|-------|----|---------------|--------------|
| LM    | 125M | 48.4 | 46.2 |
| SelfSup. | 125M | 47.2 | 51.0 |
| LM    | 1.3B | 51.8 | 50.7 |
| SelfSup. | 1.3B | 51.1 | 55.6 |

Table 9: Natural-Instructions results when combining the self-supervised tasks and the tasks in the CrossTask setting. The best performance in each column for each model size is boldfaced. MS=model size.

Table: Average results when adding denoising autoencoding and gap sentence prediction to the self-supervised training. ALL: use all of the self-supervision described in Sec. 3.

| Model | MS | QG | AG | MM | VF | Avg. |
|-------|----|----|----|----|----|------|
| LM    | 125M | 22.0 | 24.8 | 66.9 | 17.9 | 32.9 |
| CrossTask | 125M | 22.0 | 24.8 | 66.9 | 17.9 | 32.9 |
| SelfSup. | 125M | 16.9 | 14.6 | 70.1 | 18.9 | 30.0 |
| Combined | 125M | 23.5 | 25.2 | 70.3 | 18.5 | 34.4 |
| LM    | 1.3B | 41.9 | 32.5 | 74.0 | 27.8 | 43.8 |
| CrossTask | 1.3B | 38.1 | 41.6 | 69.2 | 23.0 | 42.9 |
| SelfSup. | 1.3B | 43.9 | 37.5 | 72.3 | 28.6 | 45.5 |
| Combined | 1.3B | 42.1 | 42.5 | 74.1 | 28.7 | 46.9 |

5.2 Effect of Individual Self-Supervised Tasks

We investigate the effect of individual self-supervised tasks by training models with only one of the training examples. We train the models for ten epochs. As shown in the figure, when the amount of training data for self-supervised tasks is similar to that for the CrossTask setting (i.e., 1% data), the self-supervised tasks also lead to worse performances. The improvements become clearer when we increase the number of training data, but it begins to plateau at around 100% data. This suggests that one of the advantages of the self-supervised tasks compared to the tasks in the CrossTask setting is the amount of training data. We hypothesize that further increasing the amount of data not being helpful is because the data used for constructing the self-supervised tasks has already been used for language model pretraining. So, our models manage to learn to solve these tasks with a relatively limited amount of data. We have similar observations for the 125M model. See appendix A.8 for more details.

5.3 Effect of More Self-Supervised Tasks

To investigate the effect of having more self-supervised tasks during training, we add two extra self-supervised tasks to the self-supervised training.
Table 10: Generation examples by the 1.3B model. The examples are taken from Natural-Instructions. The first two examples are from QG, and the other two are from AG. We only show part of the passages relevant to the outputs for QA for brevity.

| Task Prompt                                                                 | Task Input                                                                 | Reference                                                                 | LM                                      | Self-Supervised | Task Prompt                                                                 |
|-----------------------------------------------------------------------------|-----------------------------------------------------------------------------|---------------------------------------------------------------------------|-----------------------------------------|----------------|-----------------------------------------------------------------------------|
| Construct a question from the given fact by a simple rearrangement of words.| Fact: Pollen seeds come from male gametes of plants.                        | what seeds come from male gametes of plants?                              | What might cause harm to plants?        | What would you use to measure the number of male gametes of plants?         | Ask a question on “event duration” based on the provided sentence. |
|                                                                            |                                                                            |                                                                           |                                         |                                                            | Sentence: At the sight of the great man, Spear flushed crimson, and then his look of despair slowly disappeared; and into his eyes there came incredibly hope and gratitude. |
|                                                                            |                                                                            |                                                                           |                                         |                                                            | How long did Spear see the great man? |
|                                                                            |                                                                            |                                                                           |                                         |                                                            | How long did he stay in the Embassy? |
|                                                                            |                                                                            |                                                                           |                                         |                                                            | How long did it take for Spear to look at the great man? |
|                                                                            |                                                                            |                                                                           |                                         |                                                            | Answer the given question. Your answer must be a single span in the passage. |
|                                                                            |                                                                            | Royal Academy of Music.                                                   | Oliver.                                 | the Royal Academy of Music.                               | Answer the given question. Your answer must be a single span in the passage. |
|                                                                            |                                                                            |                                                                           |                                         |                                                            | Passage: ... The following year he won a scholarship to the Royal Academy of Music, ... The principal of the Academy, Sir Alexander Mackenzie, had forbidden ... Question: What was the full name of the school Sir Alexander Mackenzie was principal of? |
|                                                                            |                                                                            |                                                                           |                                         |                                                            | Royal Academy of Music. |
|                                                                            |                                                                            |                                                                           |                                         |                                                            | Oliver. |
|                                                                            |                                                                            |                                                                           |                                         |                                                            | the Royal Academy of Music. |
|                                                                            |                                                                            |                                                                           |                                         |                                                            | Answer the given question. Your answer must be a single span in the passage. |
|                                                                            |                                                                            | Christine Di Bella.                                                       | Di Bella.                               | many punk rock devotees.                                | Answer the given question. Your answer must be a single span in the passage. |
|                                                                            |                                                                            |                                                                           |                                         |                                                            | Passage: ... Epitaph Records, founded by Brett Gurewitz of Bad Religion, was the base for many future pop punk bands ... The mainstream pop punk of latter-day bands such as Blink-182 is criticized by many punk rock devotees; in critic Christine Di Bella’s words ... Question: What is the full name of the person that is very critical of modern mainstream pop punk bands? |
|                                                                            |                                                                            |                                                                           |                                         |                                                            | Christine Di Bella. |
|                                                                            |                                                                            |                                                                           |                                         |                                                            | the “Bad Religion”. |
|                                                                            |                                                                            |                                                                           |                                         |                                                            | many punk rock devotees. |

following the same procedure as the other tasks. The additional tasks are: denoising autoencoding (Lewis et al., 2020) and gap sentence generation (Zhang et al., 2020). Denoising autoencoding is the task of reconstructing the original sentences from sentences corrupted by random noises, which has been shown effective for training generic language representations; gap sentence generation is to recover the missing sentence and has been found useful for abstractive summarization.

We report the results in Table 6 where we do not find adding the two tasks improves downstream tasks. This is likely because the two tasks share similarities with our existing tasks (e.g., gap sentence generation shares a similar inference style as MWP). So, adding them does not promote diversity in the self-supervised tasks, leading to the fact that the models are not encouraged to learn different information.

5.4 Effect of Few-Shot Templates

The self-supervised training brings two benefits: making models familiar with the few-shot templates and task semantics. To differentiate the effect of the two, we train models on the self-supervised tasks with random labels. For example, for NSG, we use random sentences as outputs rather than the true next sentences; for the binary classification tasks, we randomly select binary labels. As shown in the results in Table 7, random labels hurt model performances, suggesting that what the models have learned is more than the few-shot templates.

We also investigate the effect of task templates for SuperGLUE by evaluating models using different templates. We report results in Table 8 where we find that having the templates for downstream tasks similar to the ones used for self-supervised training gives the models significantly better performances.

5.5 Zero-Shot vs. One-Shot vs. Few-Shot

We show zero-shot, one-shot, and few-shot performances for the LM and the self-supervised model in Table 11. We find that among the three settings, the self-supervised training is the most helpful in the few-shot setting and does not help in the zero-shot setting, suggesting that the self-supervised training improves the models’ in-context learning capabilities.
Table 11: Average results for SuperGLUE showing the zero-shot, one-shot, and few-shot model performances for the LM and the self-supervised model (SS). The numbers in parenthesis are the performance differences between the LM and the SS with the positive numbers indicating improvements. We boldface the largest improvement for each model.

![Table](image)

### 5.6 Combine Self-Supervision with Cross-Task Human-Supervision

We investigate the relations between the self-supervised tasks and the human-annotated tasks. We combine the tasks from the self-supervision and those from the CrossTask and report the results in Table 9. Interestingly, combining the two kinds of tasks results in better performances on average, showing that they are complementary.

### 5.7 Generation Examples

We show generation examples in Table 10. In general, we find that compared to the vanilla pretrained language models, the self-supervised models are better at using information from task input following task requirements. Specifically, for the first two examples in Table 10, the LM suffers from more severe semantic drift than the self-supervised model (e.g., “male gametes of plants” is more specific and relevant to the task input than “plants”). We have similar observations for the third example, where “Oliver” is a name from the task demonstration rather than the passage. Interestingly, for the last example, the answer generated by the LM is from the passage but is actually “the base for many future pop punk bands” instead of what the question looks for (i.e., “very critical of modern mainstream pop punk bands”). While the answer generated by the self-supervised model does not exactly match the reference, it is partially correct as the mainstream pop punk “is criticized by many punk rock devotees”.

### 6 Conclusion

We evaluated four self-supervised objectives on two few-shot benchmarks by casting the self-supervised training as an intermediate training stage between language model pretraining and downstream few-shot evaluation. Empirically, we have shown that the models trained by the self-supervised objectives show the best performances compared to strong baselines on average. Analysis showed that (1) the amount of self-supervised training data and the diversity of the self-supervised tasks can affect the downstream performances; (2) the self-supervised tasks are complementary to the human-annotated datasets; and (3) the self-supervised-trained models are better at following task requirements.

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A Appendix

A.1 Additional Details for LPP and Classification Tasks

The label strings we used for LPP are as follows: Yes and No, Y and N, True and False, and T and F. We randomly choose from Yes, Y, True, and T as the label string for the positive label and use the other one in the selected pair as the negative label.

The label strings we used for the binary classification task are the same as the classification LPP task. For the three-way classification task, we use the following label strings: Positive and Negative and Neutral, True and False and Neither, T and F and N, Yes and No and Unknown, Y and N and U.

A.2 Dataset Statistics

We report dataset statistics for SuperGLUE and Natural-Instructions in Table 12 and Table 13, respectively.

A.3 Training Details

We train our models in PyTorch (Paszke et al., 2017) using FAIRSEQ (Ott et al., 2019).

A.4 More Details for Natural-Instructions

Dataset Sources. CosmosQA (Huang et al., 2019), DROP (Dua et al., 2019), EssentialTerms (Khashabi et al., 2017), MCTACO (Zhou et al., 2019), MultiRC (Khashabi et al., 2018), QASC (Khot et al., 2020), Quoref (Dasigi et al., 2019), ROPES (Lee et al., 2021) and Winogrande (Sakaguchi et al., 2020).

Training Datasets. We used the following 8 datasets when training models in the cross-task setting: subtask026_drop_question_generation, subtask060ropes_question_generation, subtask028drop_answer_generation, subtask047misc_answering_science_questions, subtask046ropes_answer_generation, subtask059ropes_story_generation, subtask061ropes_answer_generation, subtask027drop_answer_typing.
Table 12: Dataset statistics for SuperGLUE. We use the official development sets as test sets.

| Dataset                      | Task Category       | Metrics                  | #Train | #Test | #Class |
|------------------------------|---------------------|--------------------------|--------|-------|--------|
| BoolQ                        | Question Answering  | Accuracy                 | 9427   | 3270  | 2      |
| MultiRC                      | Question Answering  | F1/EM                    | 5100   | 953   | 2      |
| COPA                         | Question Answering  | Accuracy                 | 400    | 100   | 2      |
| RTE                          | Natural Language Inference | Accuracy                  | 2500   | 278   | 2      |
| CB                           | Natural Language Inference | Accuracy/F1            | 250    | 57    | 3      |

Table 13: Dataset statistics for Natural-Instructions.

| Dataset                              | Task Category          | #Train | #Test | #Class |
|--------------------------------------|------------------------|--------|-------|--------|
| subtask003_mctaco_question_generation_event_duration | Question Generation | 330    | 100   |        |
| subtask004_qasc_question_generation   | Question Generation    | 6400   | 100   |        |
| subtask002_quoref_answer_generation   | Answer Generation      | 6400   | 100   |        |
| subtask033_winogrande_answer_generation | Answer Generation      | 6400   | 100   |        |
| subtask034_winogrande_question_modification_object | Minimal Modification  | 6400   | 100   |        |
| subtask045_miscellaneous_sentence_paraphrasing | Minimal Modification | 93     | 100   |        |
| subtask039_qasc_find_overlapping_words      | Verification         | 6400   | 100   |        |
| subtask044_essential_terms_identifying_essential_words | Verification      | 2138   | 100   |        |

Figure 5: Average results on SuperGLUE and Natural-Instructions when varying number of examples used for training.

A.5 List of Function Words for the Last Phrase Prediction Task

We used the following function words for identifying the last phrase: the, a, an, for, including, and, in, is, are, were, was, neither, or, nor, be, at, in, on, by, to, would, will, before, after, of, about, from, excluding, except, during, under, above, then, into, onto, should, shall, must, may, might, than, with, using, can, could, about, as, from, within, without, have, had, been.

A.6 Templates for SuperGLUE

We show the SuperGLUE templates in Table 14.

A.7 Hyperparameters

We tune the hyperparameters based on development set performances. We tune the learning rate in \{1e-7, 5e-7, 1e-6, 3e-6, 5e-6, 8e-6, 1e-5, 3e-5, 5e-5\}, and the attention dropout rate in \{0.0, 0.1\}.

A.8 Effect of Amount of Data

In Figure 5, we report model performances for the 125M and 1.3B models on SuperGLUE and Natural-Instructions with 1%, 10%, 20%, 50%, and 200% of training examples.

A.9 Effect of Individual Self-Supervised Task to Downstream Tasks

We investigate the effect of individual self-supervised task by considering two experiment settings: training models with only one task and training models with one task excluded. We report the experiment results in Table 15, Table 16, Table 17, and Table 18. Our findings are:

1. Combining all the four self-supervised tasks gives the largest improvements for most tasks, suggesting that these tasks are mostly complementary.
2. Each self-supervised task improves a few downstream task performances (e.g., NSG helps COPA; CL helps MultiRC and CB). This is likely due to the semantic similarities between tasks.
3. It is worth noting that (1) while CL hurts model performances on Natural-Instructions, it helps on the SuperGLUE; and (2) excluding NSG hurts the model performances most on Natural-Instructions whereas excluding CL hurts the most on SuperGLUE. This presumably is because SuperGLUE is ranking based and therefore is more favorable to classification-related training, whereas the tasks in Natural-Instructions are generation tasks and thus benefits more from generation-related tasks.
4. It is interesting to see that among the four self-supervised tasks, NSG and CL tasks are the two most important factors in terms of affecting the downstream performances. This is likely due to (1) the generic task formulation of NSG and it being the only sentence generation tasks; and (2) the drastic differences between CL and the other self-supervised tasks with respect to their inference styles. Unlike NSG/MWP/LPP, which models can rely on input within each example to solve the task, CL require models to make comparisons across examples in a training instance.