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Self-Instruct: Aligning Language Models with Self-Generated Instructions

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Abstract

Large "instruction-tuned" language models (i.e., finetuned to respond to instructions) have demonstrated a remarkable ability to generalize zero-shot to new tasks. Nevertheless, they depend heavily on human-written instruction data that is often limited in quantity, diversity, and creativity, therefore hindering the generality of the tuned model. We introduce Self-Instruct, a framework for improving the instruction-following capabilities of pretrained language models by bootstrapping off their own generations. Our pipeline generates instructions, input, and output samples from a language model, then filters invalid or similar ones before using them to finetune the original model. Applying our method to the vanilla GPT3, we demonstrate a 33% absolute improvement over the original model on Super-NaturalInstructions, on par with the performance of InstructGPT$_{001}$,[1] which was trained with private user data and human annotations. For further evaluation, we curate a set of expert-written instructions for novel tasks, and show through human evaluation that tuning GPT3 with Self-Instruct outperforms using existing public instruction datasets by a large margin, leaving only a 5% absolute gap behind InstructGPT$_{001}$. Self-Instruct provides an almost annotation-free method for aligning pretrained language models with instructions, and we release our large synthetic dataset to facilitate future studies on instruction tuning.[2]

```
Instruction: Given an address and city, come up
with the zip code.
Input:
Address: 123 Main Street, City: San Francisco
Output: 94105
```

```
Instruction: I am looking for a job and I need to
fill out an application form. Can you please help
me complete it?
Input:
Application Form:
Name:_________ Age:__________ Sex:________
Phone Number:______ Email Address:________
Education:___________________ ...
Output:
Name: John Doe Age: 25 Sex: Male
Phone Number: ...
```

```
Instruction: How to write a code for converting
degrees fahrenheit to celsius.
Input: Null
Output:
def convert_fahrenheit_to_celsius(fahr):
    celsius = (fahr - 32) * 5 / 9
    return celsius
```

```
Instruction: Write a letter from the perspective
of a cat.
Input: Null
Output:
Dear [Owner], I am writing to you today because I
have a problem. You see, I've been living with you
for the past [Number of Years] and I love it here.
The food is great, the bed is comfy, and there are
plenty of toys to play with. But lately, I've
noticed that you're not as affectionate towards
me as you used to be. In fact, sometimes
when I try to cuddle up next to you on the
couch, you push me away ...
```

Figure 1: Selected tasks from the generated instruction data using vanilla GPT3. Some texts are reformatted for presentation. See Table 10 for more examples.

1 Introduction

The recent NLP literature has witnessed a tremendous amount of activity in building models that can follow natural language instructions (Mishra et al., 2022; Wei et al., 2022; Sanh et al., 2022; Wang et al., 2022; Ouyang et al., 2022; Chung et al., 2022, i.a.). These developments are powered by two key components: large pretrained language models (LM) and human-written instruction data (e.g., PromptSource (Bach et al., 2022) and Super-NaturalInstructions (Wang et al., 2022, SuperNI for short)). However, collecting such instruction data is costly and often suffers limited diversity given that most human generations tend to be popular NLP tasks, falling short of covering a

[1]Unless otherwise specified, our comparisons are with the `text-davinci-001` engine. We focus on this engine since it is the closest to our experimental setup: supervised finetuning with human demonstrations. The newer engines are more powerful, though they use more data (e.g., code completion or latest user queries) or algorithms (e.g., PPO) that are difficult to compare with.

[2]Code and data are available at https://github.com/yizhongw/self-instruct

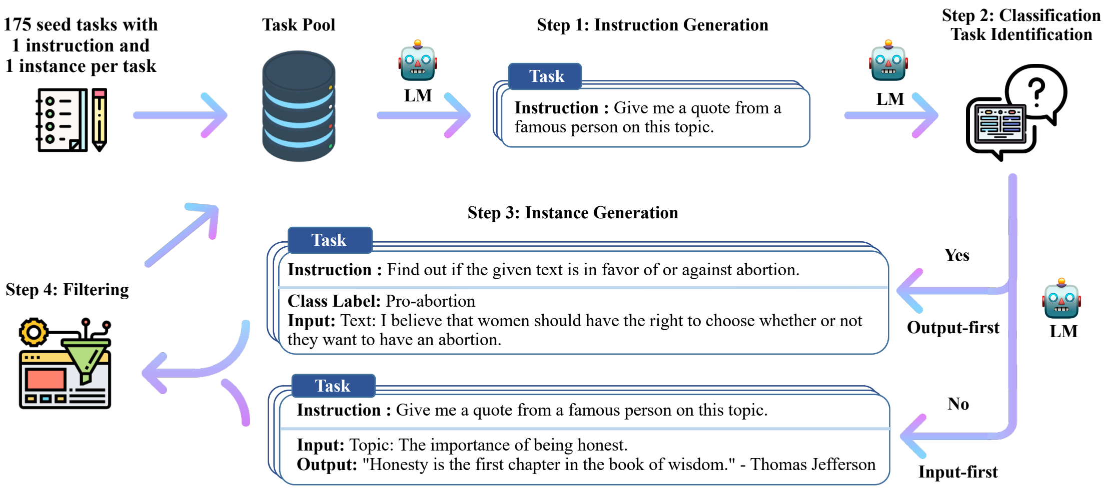

Figure 2: A high-level overview of SELF-INSTRUCT. The process starts with a small seed set of tasks as the task pool. Random tasks are sampled from the task pool, and used to prompt an off-the-shelf LM to generate both new instructions and corresponding instances, followed by filtering low-quality or similar generations, and then added back to the initial repository of tasks. The resulting data can be used for the instruction tuning of the language model itself later to follow instructions better. Tasks shown in the figure are generated by GPT3.

true variety of tasks and different ways to describe them. Continuing to improve the quality and coverage of instruction-tuned models necessitates the development of alternative approaches for supervising the instruction tuning process.

In this work, we introduce SELF-INSTRUCT, a semi-automated process for instruction-tuning a pretrained LM using instructional signals from the model itself. The overall process is an iterative bootstrapping algorithm (see Figure 2), which starts off with a limited (e.g., 175 in our study) seed set of manually-written tasks that are used to guide the overall generation. In the first phase, the model is prompted to generate instructions for new tasks. This step leverages the existing collection of instructions to create more broad-coverage instructions that define (often new) tasks. Given the newly-generated set of instructions, the framework also creates input-output instances for them, which can be later used for supervising the instruction tuning. Finally, various heuristics are used to automatically filter low-quality or repeated instructions, before adding the remaining valid tasks to the task pool. This process can be repeated for many iterations until reaching a large number of tasks.

To evaluate SELF-INSTRUCT empirically, we run this framework on GPT3 (Brown et al., 2020), which is a vanilla LM (§3). The iterative SELF-INSTRUCT process on this model leads to about 52k instructions, paired with about 82K instance inputs and target outputs. We observe that the resulting data provides a diverse range of creative tasks, as is demonstrated by examples in Figure 1. These generated tasks deviate from the distribution of typical NLP tasks, and also have fairly small overlap with the seed tasks (§3.2). On this resulting data, we build $\text{GPT3}_{\text{SELF-INST}}$ by finetuning GPT3 (i.e., the same model used for generating the instruction data). We evaluate $\text{GPT3}_{\text{SELF-INST}}$ in comparison to various other models on both typical NLP tasks included in SUPERNI (Wang et al., 2022), and a set of new instructions that are created for novel usage of instruction-following models (§4). The results indicate that $\text{GPT3}_{\text{SELF-INST}}$ outperforms GPT3 (the original model) by a large margin (+33.1%) and nearly matches the performance of InstructGPT_{001}. Moreover, our human evaluation on the newly-created instruction set shows that $\text{GPT3}_{\text{SELF-INST}}$ demonstrates a broad range of instruction following ability, outperforming models trained on other publicly available instruction datasets and leaving only a 5% gap behind InstructGPT_{001}.

In summary, our contributions are: (1) we introduce SELF-INSTRUCT, a method for inducing instruction following capabilities with minimal human-labeled data; (2) we demonstrate its effectiveness via extensive instruction-tuning experiments; and (3) we release a large synthetic dataset of 52K instructions and a set of manually-written novel tasks for building and evaluating future instruction-following models.

2 Method

Annotating large-scale instruction data can be challenging for humans because it requires 1) creativity to come up with novel tasks and 2) expertise for writing the solutions to each task. Here, we detail our process for SELF-INSTRUCT, which refers to the pipeline of generating tasks with a *vanilla pretrained language model* itself, filtering the generated data, and then conducting instruction tuning with this generated data in order to align the LM to follow instructions better. This pipeline is depicted in Figure 2.

2.1 Defining Instruction Data

The instruction data we want to generate contains a set of instructions $\{I_t\}$, each of which defines a task t in natural language. Task t has $n_t \geq 1$ input-output instances $\{(X_{t,i}, Y_{t,i})\}_{i=1}^{n_t}$. A model M is expected to produce the output, given the task instruction and the corresponding input: $M(I_t, X_{t,i}) = Y_{t,i}$, for $i \in \{1, \ldots, n_t\}$. Note that the instruction and instance input does not have a strict boundary in many cases. For example, "write an essay about school safety" can be a valid instruction that we expect models to respond to directly, while it can also be formulated as "write an essay about the following topic" as the instruction, and "school safety" as an instance input. To encourage the diversity of the data format, we allow such instructions that do not require additional input (i.e., X is empty).

2.2 Automatic Instruction Data Generation

Our pipeline for data generation consists of four steps: 1) generating task instructions, 2) determining if the instruction represents a classification task, 3) instance generation with either an input-first or output-first approach, and 4) filtering low-quality data.

Instruction Generation. At the first step, SELF-INSTRUCT generates new instructions from a small set of seed human-written instructions in a bootstrapping fashion. We initiate the task pool with 175 tasks (1 instruction and 1 instance for each task).[3] For every step, we sample 8 task instructions from this pool as in-context examples. Of the 8 instructions, 6 are from the human-written tasks, and 2 are from the model-generated tasks in previous steps to promote diversity. The prompting template is shown in Table 5.

Classification Task Identification. Because we need two different approaches for classification and non-classification tasks, we next identify whether the generated instruction represents a classification task or not.[4] We prompt the LM in a few-shot way to determine this, using 12 classification instructions and 19 non-classification instructions from the seed tasks. The prompting template is shown in Table 6.

Instance Generation. Given the instructions and their task type, we generate instances for each instruction independently. This is challenging because it requires the model to understand what the target task is, based on the instruction, figure out what additional input fields are needed and generate them, and finally complete the task by producing the output. We found that pretrained LMs can achieve this to a large extent when prompted with instruction-input-output in-context examples from other tasks. A natural way to do this is the **Input-first Approach**, where we can ask an LM to come up with the input fields first based on the instruction, and then produce the corresponding output. This generation order is similar to how models are used to respond to instruction and input, but here with in-context examples from other tasks. The prompting template is shown in Table 7.

However, we found that this approach can generate inputs biased toward one label, especially for classification tasks (e.g., for grammar error detection, it usually generates grammatical input). Therefore, we additionally propose an **Output-first Approach** for classification tasks, where we first generate the possible class labels, and then condition the input generation on each class label. The prompting template is shown in Table 8.[5] We apply the output-first approach to the classification tasks identified in the former step, and the input-first approach to the remaining non-classification tasks.

Filtering and Postprocessing. To encourage diversity, a new instruction is added to the task pool only when its ROUGE-L similarity with any exist-

[3] These tasks were newly written by the authors and their labmates at UW, without reference to existing datasets or the test set used in this work. We provide more details about these tasks and analyze their similarity to the test tasks in Appendix §A.1.

[4] More concretely, we regard tasks that have a small limited output label space as classification tasks.

[5] In this work, we use a fixed set of seed tasks for prompting the instance generation, and thus only generate a small number of instances per task in one round. Future work can use randomly sampled tasks to prompt the model to generate a larger number of instances in multiple rounds.

ing instruction is less than 0.7. We also exclude instructions that contain some specific keywords (e.g., image, picture, graph) that usually can not be processed by LMs. When generating new instances for each instruction, we filter out instances that are exactly the same or those with the same input but different outputs. Invalid generations are identified and filtered out based on heuristics (e.g., instruction is too long or too short, instance output is a repetition of the input).

2.3 Finetuning the LM to Follow Instructions

After creating large-scale instruction data, we use it to finetune the original LM (i.e., SELF-INSTRUCT). To do this, we concatenate the instruction and instance input as a prompt and train the model to generate the instance output in a standard supervised way. To make the model robust to different formats, we use multiple templates to encode the instruction and instance input together. For example, the instruction can be prefixed with "Task:" or not, the input can be prefixed with "Input:" or not, "Output:" can be appended at the end of the prompt or not, and different numbers of break lines can be put in the middle, etc.

3 SELF-INSTRUCT Data from GPT3

In this section, we apply our method for inducing instruction data to GPT3 as a case study. We use the largest GPT3 LM ("davinci" engine) accessed through the OpenAI API.[6] The parameters for making queries are described in Appendix A.2. Here we present an overview of the generated data.

3.1 Statistics

Table 1 describes the basic statistics of the generated data. We generate a total of over 52K instructions and more than 82K instances corresponding to these instructions after filtering.

statistic	
# of instructions	52,445
- # of classification instructions	11,584
- # of non-classification instructions	40,861
# of instances	82,439
- # of instances with empty input	35,878
ave. instruction length (in words)	15.9
ave. non-empty input length (in words)	12.7
ave. output length (in words)	18.9

Table 1: Statistics of the generated data by applying SELF-INSTRUCT to GPT3.

[6]https://openai.com/api/

3.2 Diversity

To study what types of instructions are generated and how diverse they are, we identify the verb-noun structure in the generated instructions. We use the Berkeley Neural Parser[7] (Kitaev and Klein, 2018; Kitaev et al., 2019) to parse the instructions and then extract the verb that is closest to the root as well as its first direct noun object. 26,559 out of the 52,445 instructions contain such structure; other instructions usually contain more complex clauses (e.g., "Classify whether this tweet contains political content or not.") or are framed as questions (e.g., "Which of these statements are true?"). We plot the top 20 most common root verbs and their top 4 direct noun objects in Figure 3, which account for 14% of the entire set. Overall, we see quite diverse intents and textual formats in these instructions.

We further study how the generated instructions differ from the seed instructions used to prompt the generation. For each generated instruction, we compute its highest ROUGE-L overlap with the 175 seed instructions. We plot the distribution of these ROUGE-L scores in Figure 4. The results indicate a decent number of new instructions were generated, which do not have much overlap with the seeds. We also demonstrate diversity in the length of the instructions, instance inputs, and instance outputs in Figure 5.

3.3 Quality

So far, we have shown the quantity and diversity of the generated data, but its quality remains uncertain. To investigate this, we randomly sample 200 instructions and randomly select 1 instance per instruction. We asked an expert annotator (author of this work) to label whether each instance is correct or not, in terms of the instruction, the instance input, and the instance output. Evaluation results in Table 2 show that most of the generated instructions are meaningful, while the generated instances may contain more noise (to a reasonable extent). However, we found that even though the generations may contain errors, most of them are still in the correct format or partially correct, which can provide useful guidance for training models to follow instructions. We listed a number of good examples and bad examples in Table 10 and 11, respectively.

[7]https://parser.kitaev.io/

Figure 3: The top 20 most common root verbs (inner circle) and their top 4 direct noun objects (outer circle) in the generated instructions. Despite their diversity, the instructions shown here only account for 14% of all the generated instructions because many instructions (e.g., “Classify whether the user is satisfied with the service.”) do not contain such a verb-noun structure.

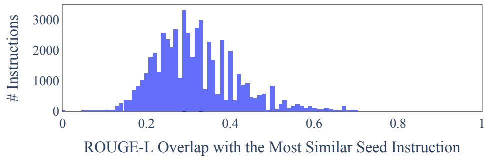

Figure 4: Distribution of the ROUGE-L scores between generated instructions and their most similar seed instructions.

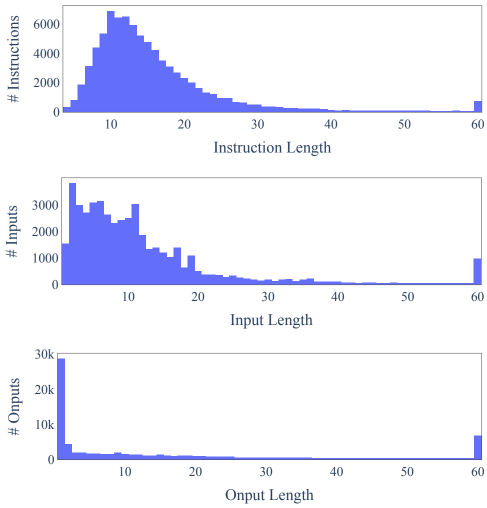

Figure 5: Length distribution of the generated instructions, non-empty inputs, and outputs.

Quality Review Question	Yes %
Does the instruction describe a valid task?	92%
Is the input appropriate for the instruction?	79%
Is the output a correct and acceptable response to the instruction and input?	58%
All fields are valid	54%

Table 2: Data quality review for the instruction, input, and output of the generated data. See Table 10 and Table 11 for representative valid and invalid examples.

4 Experimental Results

We conduct experiments to measure and compare the performance of models under various instruction tuning setups. We first describe our models and other baselines, followed by our experiments.

4.1 GPT3$_{\text{SELF-INST}}$: finetuning GPT3 on its own instruction data

Given the instruction-generated instruction data, we conduct instruction tuning with the GPT3 model itself (“davinci” engine). As described in §2.3, we use various templates to concatenate the instruction and input, and train the model to generate the output. This finetuning is done through the OpenAI finetuning API.[8] We use the default hyper-parameters, except that we set the prompt loss weight to 0, and we train the model for 2 epochs. We refer the reader to Appendix A.3 for additional finetuning details. The resulting model is denoted by GPT3$_{\text{SELF-INST}}$.

4.2 Baselines

Off-the-shelf LMs. We evaluate T5-LM (Lester et al., 2021; Raffel et al., 2020) and GPT3 (Brown et al., 2020) as the vanilla LM baselines (only pre-training, no additional finetuning). These baselines will indicate the extent to which off-the-shelf LMs are capable of following instructions naturally immediately after pretraining.

Publicly available instruction-tuned models. T0 and T*k*-INSTRUCT are two instruction-tuned models proposed in Sanh et al. (2022) and Wang et al. (2022), respectively, and are demonstrated to be able to follow instructions for many NLP tasks. Both of these models are finetuned from the T5 (Raffel et al., 2020) checkpoints and are publicly available.[9] For both of these models, we use

[8]See OpenAI’s documentation on finetuning.

[9]T0 is available at here and T*k*-INSTRUCT is here.

their largest version with 11B parameters.

Instruction-tuned GPT3 models. We evaluate InstructGPT (Ouyang et al., 2022), which is developed by OpenAI based on GPT3 to follow human instructions better and has been found by the community to have impressive zero-shot abilities. There are various generations of these models, where newer ones use more expansive data or algorithmic novelties.[10] For our SUPERNI experiments in §4.3, we only compare with their `text-davinci-001` engine, because their newer engines are trained with the latest user data and are likely to have already seen the SUPERNI test set. For our human evaluation on newly written instructions, we include their 001, 002 and 003 engines for completeness.

Additionally, to compare SELF-INSTRUCT training with other publicly available instruction tuning data, we further finetune GPT3 model with data from PROMPTSOURCE and SUPERNI, which are used to train the T0 and T*k*-INSTRUCT models. We call them T0 training and SUPERNI training for short, respectively. To save the training budget, we sampled 50K instances (but covering all their instructions) for each dataset, which has a comparable size to the instruction data we generated. Based on the findings from Wang et al. (2022) and our early experiments, reducing the number of instances per training task does not degrade the model's generalization performance to unseen tasks.

4.3 Experiment 1: Zero-Shot Generalization on SUPERNI benchmark

We first evaluate the models' ability to follow instructions on typical NLP tasks in a zero-shot fashion. We use the evaluation set of SUPERNI (Wang et al., 2022), which consists of 119 tasks with 100 instances in each task. In this work, we mainly focus on the zero-shot setup, i.e., the model is prompted with the definition of the tasks only, without in-context demonstration examples. For all our requests to the GPT3 variants, we use the deterministic generation mode (temperature as 0 and no nucleus sampling) without specific stop sequences.

Results. We make the following observations from the results in Table 3. SELF-INSTRUCT boosts the instruction-following ability of GPT3 by a large margin. The vanilla GPT3 model basically cannot follow human instructions at all. Upon manual analysis, we find that it usually generates irrelevant and repetitive text, and does not know when to stop generation. Compared with other models that are not specifically trained for SUPERNI, GPT3$_{\text{SELF-INST}}$ achieves better performance than T0 or the GPT3 finetuned on the T0 training set, which takes tremendous human labeling efforts. Notably, GPT3$_{\text{SELF-INST}}$ also nearly matches the performance of InstructGPT$_{001}$, which is trained with private user data and human-annotated labels.

	Model	# Params	ROUGE-L
	Vanilla LMs		
	T5-LM	11B	25.7
	GPT3	175B	6.8
	Instruction-tuned w/o SUPERNI		
①	T0	11B	33.1
	GPT3 + T0 Training	175B	37.9
②	GPT3$_{\text{SELF-INST}}$ (Ours)	175B	39.9
	InstructGPT$_{001}$	175B	**40.8**
	Instruction-tuned w/ SUPERNI		
	T*k*-INSTRUCT	11B	46.0
③	GPT3 + SUPERNI Training	175B	49.5
	GPT3$_{\text{SELF-INST}}$ + SUPERNI Training (Ours)	175B	**51.6**

Table 3: Evaluation results on *unseen* tasks from SUPERNI (§4.3). From the results, we see that ① SELF-INSTRUCT can boost GPT3 performance by a large margin (+33.1%) and ② nearly matches the performance of InstructGPT$_{001}$. Additionally, ③ it can further improve the performance even when a large amount of labeled instruction data is present.

Models trained on the SUPERNI training set still achieve better performance on its evaluation set, which we attribute to the similar instruction style and formatting. However, we show that SELF-INSTRUCT still brings in additional gains when combined with the SUPERNI training set, proving its value as complementary data.

4.4 Experiment 2: Generalization to User-oriented Instructions on Novel Tasks

Despite the comprehensiveness of SUPERNI in collecting existing NLP tasks, most of these NLP tasks were proposed for research purposes and skewed toward classification. To better access the practical value of instruction-following models, a subset of the authors curate a new set of instructions motivated by user-oriented applications. We first brainstorm various domains where large LMs may be useful (e.g., email writing, social media, productivity tools, entertainment, programming), then craft instructions related to each domain along with an input-output instance (again, input is optional). We aim to diversify the styles and formats of these tasks (e.g., instructions may be long or short; in-

[10] See OpenAI's documentation on their models.

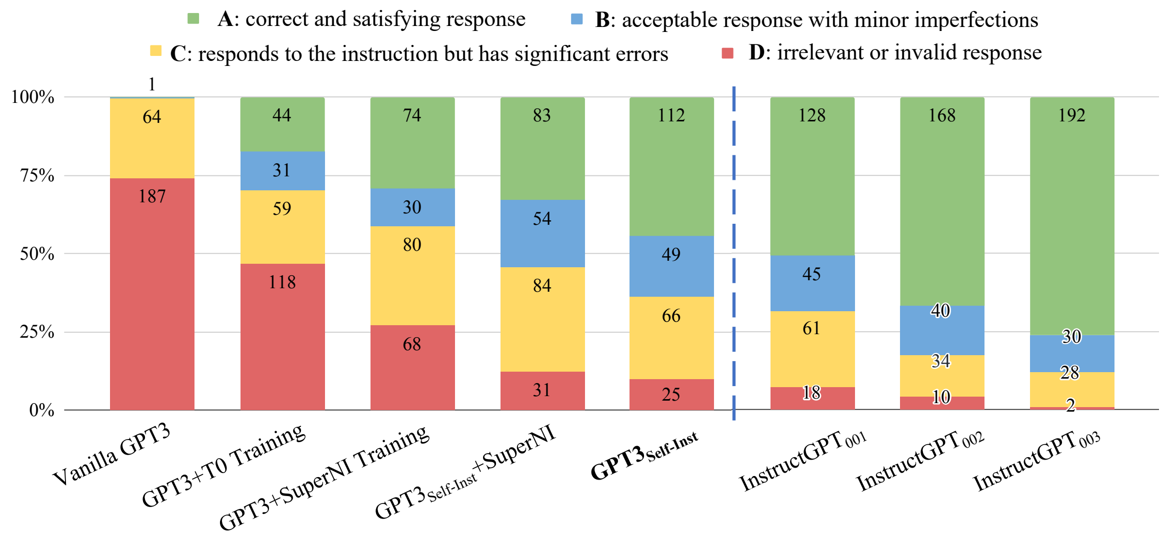

Figure 6: Performance of GPT3 model and its instruction-tuned variants, evaluated by human experts on our 252 user-oriented instructions (§4.4). Human evaluators are instructed to rate the models' responses into four levels. The results indicate that $\text{GPT3}_{\text{SELF-INST}}$ outperforms all the other GPT3 variants trained on publicly available instruction datasets. Additionally, $\text{GPT3}_{\text{SELF-INST}}$ scores nearly as good as InstructGPT_{001} (cf. footnote 1).

put/output may take the form of bullet points, tables, codes, equations, etc.). In total, we create 252 instructions with 1 instance per instruction. We believe it can serve as a testbed for evaluating how instruction-based models handle diverse and unfamiliar instructions. Table 9 presents a small portion of them. The entire set is available in our GitHub repository. We analyze the overlap between this set set and the seed instructions in §A.1.

Human evaluation setup. Evaluating models' performance on this evaluation set of diverse tasks is extremely challenging because different tasks require different expertise. Indeed, many of these tasks cannot be measured by automatic metrics or even be judged by normal crowdworkers (e.g., writing a program, or converting first-order logic into natural language). To get a more faithful evaluation, we asked the authors of the instructions to judge model predictions. Details on how we set up this human evaluation are described in Appendix B. The evaluators were asked to rate the output based on whether it accurately and effectively completes the task. We implemented a four-level rating system for categorizing the quality of the models' outputs:

- RATING-A: The response is valid and satisfying.
- RATING-B: The response is acceptable but has minor errors or imperfections.
- RATING-C: The response is relevant and responds to the instruction, but it has significant errors in the content. For example, GPT3 might generate a valid output first, but continue to generate other irrelevant things.
- RATING-D: The response is irrelevant or completely invalid.

Results. Figure 6 shows the performance of GPT3 model and its instruction-tuned counterparts on this newly written instruction set (w. inter-rater agreement $\kappa = 0.57$ on the 4-class categorical scale, see Appendix B for details). As anticipated, the vanilla GPT3 LM is largely unable to respond to instructions, and all instruction-tuned models demonstrate comparatively higher performance. Nonetheless, $\text{GPT3}_{\text{SELF-INST}}$ (i.e., GPT3 model finetuned with SELF-INSTRUCT) outperforms those counterparts trained on T0 or SUPERNI data by a large margin, demonstrating the value of the generated data despite the noise. Compared with InstructGPT_{001}, $\text{GPT3}_{\text{SELF-INST}}$ is quite close in performance—if we count acceptable response with minor imperfections (RATING-B) as valid, $\text{GPT3}_{\text{SELF-INST}}$ is only 5% behind InstructGPT_{001}. Lastly, our evaluation confirms the impressive instruction-following ability of InstructGPT_{002} and InstructGPT_{003}. Although there are many factors behind this success, we conjecture that future work can largely benefit from improving the quality of our generated data by using human annotators or training a reward model to select better generations, similar to the algorithm used by Ouyang et al. (2022).

4.5 Effect of Data Size and Quality

Data size. SELF-INSTRUCT provides a way to grow instruction data at a low cost with almost no human labeling; could more of this generated data lead to better instruction-following ability? We conduct an analysis of the size of generated data by subsampling different numbers of instructions from the generated dataset, finetuning GPT3 on the sampled subsets, and evaluating how the resulting models perform on the 252 user-oriented instruction set. We conduct the same human evaluation as in §4.4. Figure 7 presents the performance of GPT3$_{\text{SELF-INST}}$ models finetuned with different sizes of generated data. Overall, we see consistent improvement as we grow the data size. However, this improvement almost plateaus after 16K. This is in-line with the data scaling experiments in Wang et al. (2022, Fig. 5). Interestingly, when evaluating on SUPERNI we found the model's performance gain plateaus earlier at around hundreds of instructions. This may be due to the fact that the new generated data is distinct from typical NLP tasks in SUPERNI, indicating that future research may benefit from using a combination of different instruction data for better performance on various types of tasks.

Data quality. Another direction to improve the model's performance is to take our generated data and get better supervision (with less noise). We explore this idea by using InstructGPT$_{003}$ (the best available general-purpose model) to regenerate the output field of all our instances given the instruction and input. We then use this improved version of our data to finetune GPT3. This can be regarded as a distillation of InstructGPT$_{003}$ with our data. As is shown in Figure 7, the resulting model outperforms the counterpart trained with the original data by 10%, which suggests big room for future work on using our generation pipeline to get initial data and then improving the data quality with human experts or distillation from better models.

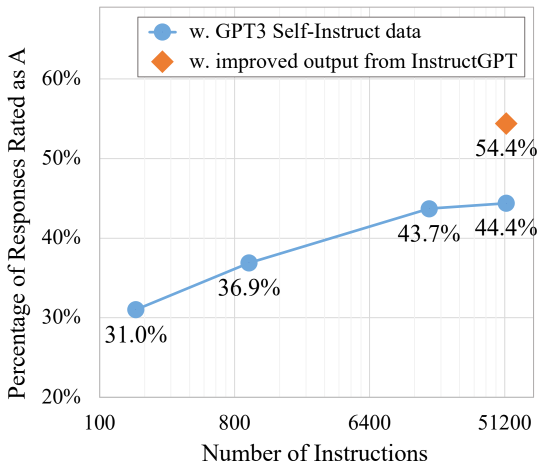

Figure 7: Human evaluation performance of GPT3$_{\text{SELF-INST}}$ models tuned with different sizes of instructions. x-axis is in log scale. The smallest size is 175, where only the seed tasks are used for instruction tuning. We also evaluate whether improving the data quality will further improve the performance by distilling the outputs from InstructGPT$_{003}$. We see consistent improvement from using larger data with better quality.

5 Related Work

Instruction-following LMs. A series of works have found evidence that vanilla LMs can be effective at following general language instructions if tuned with annotated "instructional" data—datasets containing language instructional commands and their desired outcomes based on human annotation (Weller et al., 2020; Mishra et al., 2022; Wei et al., 2022; Sanh et al., 2022, i.a.). Additionally, they show a direct correlation between the size and diversity of the "instructional" data and the generalizability of resulting models to unseen tasks (Wang et al., 2022; Chung et al., 2022). However, since these developments largely focus on existing NLP tasks and depend on human-annotated instructions, this poses a bottleneck for progress toward more generalizable models (e.g., see Fig. 5a in Wang et al., 2022). Our work aims to move beyond classical NLP tasks and tackle the challenges of creating diverse instruction data by employing pretrained LMs. InstructGPT (Ouyang et al., 2022) shares a similar goal as ours in building more general-purpose LMs, and has demonstrated remarkable performance in following diverse user instructions. However, as a commercial system, their construction process still remains quite opaque. In particular, the role of *data* has remained understudied due to limited transparency and the private user data they used in their study. Addressing such challenges necessitates the creation of a large-scale, public dataset covering a broad range of tasks.

Language models for data generation and augmentation. A variety of works have proposed using LMs for data generation (Schick and Schütze, 2021; Wang et al., 2021; Liu et al., 2022; Meng et al., 2023) or augmentation (Feng et al., 2021; Yang et al., 2020; Mekala et al., 2022). Our work differs from this line in that it is *not* specific to a particular task (say, QA or NLI). In contrast, a distinct motivation for SELF-INSTRUCT is to bootstrap new task definitions that may not have been defined before by NLP practitioners (though potentially still important for real users). In parallel with our work, Honovich et al. (2022a) also propose to generate large-scale instruction data (so-called Unnatural Instructions) with GPT3 models. The major differences are that 1) they use tasks in SUPERNI (Wang et al., 2022) as their seed tasks, resulting in a different distribution of generated tasks; 2) they employ InstructGPT_{002} for generating the data, in which sense they are distilling knowledge from an already instruction-tuned model, while we solely rely on the vanilla LM; 3) the detailed generation pipeline and templates are different. Nevertheless, we believe that both efforts in expanding instruction data are complementary, and the community will benefit from these diverse datasets.

Instruction generation. A series of recent works (Zhou et al., 2022b; Ye et al., 2022; Singh et al., 2022; Honovich et al., 2022b) generate instructions of a task given a few examples. While SELF-INSTRUCT also involves instruction generation, a major difference in our case is it is task-agnostic; we generate new tasks (instructions along with instances) from scratch.

Model self-training. A typical self-training framework (He et al., 2019; Xie et al., 2020; Du et al., 2021; Amini et al., 2022; Huang et al., 2022) uses trained models to assign labels to unlabeled data and then leverages the newly labeled data to improve the model. In a similar line, Zhou et al. (2022a) use multiple prompts to specify a single task and propose to regularize via prompt consistency, encouraging consistent predictions over the prompts. This allows either finetuning the model with extra unlabeled training data, or direct application at inference time. While SELF-INSTRUCT has similarities with the self-training literature, most self-training methods assume a specific *target task* as well as *unlabeled examples* under it; in contrast, SELF-INSTRUCT produces a variety of tasks from scratch.

Knowledge distillation. Knowledge distillation (Hinton et al., 2015; Sanh et al., 2019; West et al., 2021; Magister et al., 2022) often involves the transfer of knowledge from larger models to smaller ones. SELF-INSTRUCT can also be viewed as a form of "knowledge distillation", however, it differs from this line in the following ways: (1) the source and target of distillation are the same, i.e., a model's knowledge is distilled to itself; (2) the content of distillation is in the form of an instruction task (i.e., instructions that define a task, and a set of examples that instantiate it).

Bootstrapping with limited resources. A series of recent works use language models to bootstrap some inferences using specialized methods. NPPrompt (Zhao et al., 2022) provides a method to generate predictions for semantic labels without any finetuning. It uses a model's own embeddings to automatically find words relevant to the label of the data sample and hence reduces the dependency on manual mapping from model prediction to label (verbalizers). STAR (Zelikman et al., 2022) iteratively leverages a small number of rationale examples and a large dataset without rationales, to bootstrap a model's ability to perform reasoning. Self-Correction (Welleck et al., 2023) decouples an imperfect base generator (model) from a separate corrector that learns to iteratively correct imperfect generations and demonstrates improvement over the base generator. Our work instead focuses on bootstrapping new tasks in the instruction paradigm.

Multi-modal instruction-following. Instruction-following models have also been of interest in the multi-modal learning literature (Fried et al., 2018; Shridhar et al., 2020; Min et al., 2022; Weir et al., 2022). SELF-INSTRUCT, as a general approach to expanding data, can potentially also be helpful in those settings, which we leave to future work.

6 Conclusion

We introduce SELF-INSTRUCT, a method to improve the instruction-following ability of LMs via their own generation of instruction data. On experimenting with vanilla GPT3, we automatically construct a large-scale dataset of 52K instructions for diverse tasks, and finetuning GPT3 on this data leads to a 33% absolute improvement on SUPERNI over the original GPT3. Furthermore, we curate a set of expert-written instructions for novel tasks. Human evaluation on this set shows that tuning GPT3 with SELF-INSTRUCT outperforms using existing public instruction datasets by a large margin and performs closely to InstructGPT_{001}. We hope SELF-INSTRUCT can serve as the first step to align pretrained LMs to follow human instructions, and future work can build on top of this data to improve instruction-following models.

7 Broader Impact

Beyond the immediate focus of this paper, we believe that SELF-INSTRUCT may help bring more transparency to what happens "behind the scenes" of widely-used instruction-tuned models like InstructGPT or ChatGPT. Unfortunately, such industrial models remain behind API walls as their datasets are not released, and hence there is little understanding of their construction and why they demonstrate impressive capabilities. The burden now falls on academia to better understand the source of success in these models and strive for better—and more open—models. We believe our findings in this paper demonstrate the importance of diverse instruction data, and our large synthetic dataset can be the first step toward higher-quality data for building better instruction-following models. At this writing, the central idea of this paper has been adopted in several follow-up works for such endeavors (Taori et al., 2023; Xu et al., 2023; Sun et al., 2023, i.a.).

8 Limitations

Here, we discuss some limitations of this work to inspire future research in this direction.

Tail phenomena. SELF-INSTRUCT depends on LMs, and it will inherit all the limitations that carry over with LMs. As recent studies have shown (Razeghi et al., 2022; Kandpal et al., 2022), *tail phenomena* pose a serious challenge to the success of LMs. In other words, LMs' largest gains correspond to the frequent uses of languages (head of the language use distribution), and there might be minimal gains in the low-frequency contexts. Similarly, in the context of this work, it would not be surprising if the majority of the gains by SELF-INSTRUCT are skewed toward tasks or instructions that present more frequently in the pretraining corpus. As a consequence, the approach might show brittleness with respect to uncommon and creative instructions.

Dependence on large models. Because of SELF-INSTRUCT's dependence on the inductive biases extracted from LMs, it might work best for larger models. If true, this may create barriers to access for those who may not have large computing resources. We hope future studies will carefully study the gains as a function of model size or various other parameters. It is worthwhile to note that instruction-tuning with human annotation also suffers from a similar limitation: gains of instruction-tuning are higher for larger models (Wei et al., 2022).

Reinforcing LM biases. A point of concern for the authors is the unintended consequences of this iterative algorithm, such as the amplification of problematic social biases (stereotypes or slurs about gender, race, etc.). Relatedly, one observed challenge in this process is the algorithm's difficulty in producing balanced labels, which reflected models' prior biases. We hope future work will lead to better understanding of the pros and cons of the approach.

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Supplemental Material

A Implementation Details

A.1 Writing the Seed Tasks

Our method relies on a set of seed tasks to bootstrap the generation. The seed tasks are important for both encouraging the task diversity and demonstrating correct ways for solving the diverse tasks. For example, with coding tasks to prompt the model, it has a larger chance to generate coding-related tasks; it's also better to have coding output to guide the model in writing code for new tasks. So, the more diverse the seed tasks are, the more diverse and better quality the generated tasks will be.

Our seed tasks were written when we initiated this project, and targeted for the diverse and interesting usages of LLMs. The tasks were written by the authors and our labmates at UWNLP, without explicit reference to existing datasets or specific testing tasks. We further categorized the tasks into classification and non-classification tasks, based on whether the task has a limited output label space. In total, there are 25 classification tasks and 150 non-classification tasks. We release this data in our GitHub repository.[11]

To provide a sense of how much the model is generalizing beyond these seed tasks, we further quantify the overlap between the instructions of these seed tasks and the instructions of our test sets, including both SUPERNI task instructions (§4.3) and the user-oriented instructions in our human evaluation(§4.4). We compute ROUGE-L similarities between each seed instruction and its most similar instruction in the test set. The distribution of the ROUGE-L scores are plotted in Figure 8, with the average ROUGE-L similarity between the seed instructions and SUPERNI as 0.21, and the average ROUGE-L similarity between the seed instructions and user-oriented instructions as 0.34. We see a decent difference between the seed tasks and both test sets. There is exactly one identical seed instruction occurring in the user-oriented instruction test set, which is "answer the following question" and the following questions are actually very different.

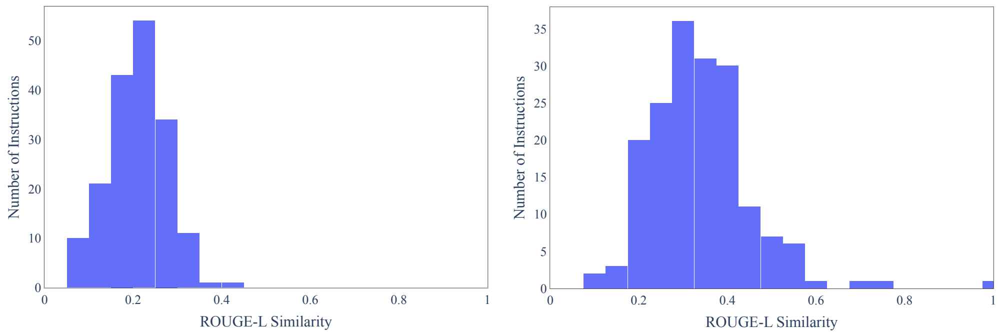


Figure 8: Distribution of the ROUGE-L scores between seed instructions and their most similar instructions in SUPERNI (left) and the 252 user-oriented instructions (right).

A.2 Querying the GPT3 API

We use different sets of hyperparameters when querying GPT3 API for different purposes. These hyperparameters are found to work well with the GPT3 model ("davinci" engine) and the other instruction-tuned GPT3 variants. We listed them in Table 4. OpenAI charges $0.02 per 1000 tokens for making completion request to the "davinci" engine as of December, 2022. The generation of our entire dataset cost around $600.

A.3 Finetuning GPT3

$\text{GPT3}_{\text{SELF-INST}}$ and some of our baselines are finetuned from GPT3 model ("davinci" engine with 175B parameters). We conduct this finetuning via OpenAI's finetuning API.[12] While the details of how the model is finetuned with this API are not currently available (e.g., which parameters are updated, or what

[11] https://github.com/yizhongw/self-instruct/blob/main/human_eval/user_oriented_instructions.jsonl

[12] See the the details on OpenAI's API.

Experiments ↓	Temp.	Top_P	Freq. Penalty	Presence Penalty	Beam Size	Max Length	Stop Sequences
Generating instructions	0.7	0.5	0	2	1	1024	"\n\n", "\n16", "16.", "16 ."
Identifying clf. tasks	0	0	0	0	1	3	"\n", "Task:"
Generating instances	0	0	0	1.5	1	300	"Task:"
Evaluating models	0	0	0	0	0	1024	None (default)

Table 4: Hyper-parameters for querying OpenAI API in different experiments.

the optimizer is), we tune all our models with the default hyperparameters of this API so that the results are comparable. We only set the "prompt_loss_weight" to 0 since we find this works better in our case, and every finetuning experiment is trained for two epochs to avoid overfitting the training tasks. Finetuning is charged based on the number of tokens in the training file. In our case, finetuning $\text{GPT3}_{\text{SELF-INST}}$ from the GPT3 model on the entire generated data cost $338.

A.4 Prompting Templates for Data Generation

SELF-INSTRUCT relies on a number of prompting templates in order to elicit the generation from language models. Here we provide our four templates for generating the instruction (Table 5), classifying whether an instruction represents a classification task or not (Table 6), generating non-classification instances with the input-first approach (Table 7), and generating classification instances with the output-first approach (Table 8).

```
Come up with a series of tasks:

Task 1:  {instruction for existing task 1}
Task 2:  {instruction for existing task 2}
Task 3:  {instruction for existing task 3}
Task 4:  {instruction for existing task 4}
Task 5:  {instruction for existing task 5}
Task 6:  {instruction for existing task 6}
Task 7:  {instruction for existing task 7}
Task 8:  {instruction for existing task 8}
Task 9:
```

Table 5: Prompt used for generating new instructions. 8 existing instructions are randomly sampled from the task pool for in-context demonstration. The model is allowed to generate instructions for new tasks, until it stops its generation, reaches its length limit or generates "Task 16" tokens.

```
Can the following task be regarded as a classification task with finite output labels?

Task:  Given my personality and the job, tell me if I would be suitable.
Is it classification?  Yes

Task:  Give me an example of a time when you had to use your sense of humor.
Is it classification?  No

Task:  Replace the placeholders in the given text with appropriate named entities.
Is it classification?  No

Task:  Fact checking - tell me if the statement is true, false, or unknown, based on your
knowledge and common sense.
Is it classification?  Yes

Task:  Return the SSN number for the person.
Is it classification?  No

Task:  Detect if the Reddit thread contains hate speech.
Is it classification?  Yes

Task:  Analyze the sentences below to identify biases.
Is it classification?  No

Task:  Select the longest sentence in terms of the number of words in the paragraph, output
the sentence index.
Is it classification?  Yes

Task:  Find out the toxic word or phrase in the sentence.
Is it classification?  No

Task:  Rank these countries by their population.
Is it classification?  No

Task:  You are provided with a news article, and you need to identify all the categories that
this article belongs to.  Possible categories include:  Music, Sports, Politics, Tech, Finance,
Basketball, Soccer, Tennis, Entertainment, Digital Game, World News.  Output its categories one
by one, seperated by comma.
Is it classification?  Yes

Task:  Given the name of an exercise, explain how to do it.
Is it classification?  No

Task:  Select the oldest person from the list.
Is it classification?  Yes

Task:  Find the four smallest perfect numbers.
Is it classification?  No

Task:  Does the information in the document supports the claim?  You can answer "Support" or
"Unsupport".
Is it classification?  Yes

Task:  Create a detailed budget for the given hypothetical trip.
Is it classification?  No

Task:  Given a sentence, detect if there is any potential stereotype in it.  If so, you should
explain the stereotype.  Else, output no.
Is it classification?  No

...

Task:  To make the pairs have the same analogy, write the fourth word.
Is it classification?  No

Task:  Given a set of numbers, find all possible subsets that sum to a given number.
Is it classification?  No

Task:  {instruction for the target task}
```

Table 6: Prompt used for classifying whether a task instruction is a classification task or not.

```
Come up with examples for the following tasks. Try to generate multiple examples when possible.
If the task doesn't require additional input, you can generate the output directly.

Task: Which exercises are best for reducing belly fat at home?
Output:
- Lying Leg Raises
- Leg In And Out
- Plank
- Side Plank
- Sit-ups

Task: Extract all the country names in the paragraph, list them separated by commas.
Example 1
Paragraph: Dr. No is the sixth novel by the English author Ian Fleming to feature his British
Secret Service agent James Bond. Written at Fleming's Goldeneye estate in Jamaica, it was
first published in the United Kingdom by Jonathan Cape in 1958. In the novel Bond looks into
the disappearance in Jamaica of two fellow MI6 operatives who had been investigating Doctor
No. Bond travels to No's Caribbean island and meets Honeychile Rider, who is there to collect
shells. They are captured and taken to a luxurious facility carved into a mountain. The
character of Doctor No, the son of a German missionary and a Chinese woman, was influenced by
Sax Rohmer's Fu Manchu stories. Dr. No was the first of Fleming's novels to face widespread
negative reviews in Britain, but it was received more favourably in the United States.
Output: English, British, Jamaica, the United Kingdom, German, Chinese, Britain, the United
States.

Task: Converting 85 F to Celsius.
Output: 85°F = 29.44°C

Task: Sort the given list ascendingly.
Example 1
List: [10, 92, 2, 5, -4, 92, 5, 101]
Output: [-4, 2, 5, 5, 10, 92, 92, 101]
Example 2
Input 2 - List: [9.99, 10, -5, -1000, 5e6, 999]
Output: [-1000, -5, 9.99, 10, 999, 5e6]

Task: Suggest a better and more professional rephrasing of the following sentence.
Example 1
Sentence: This house is surprisingly not constructed very well, and you probably need more
money to fix it after you buy it. If you ask me, I would suggest you to consider other
candidates.
Output: This house does not seem to be constructed well, so you may need to spend more money
to fix it after you purchase it. I would suggest that you look at other properties.
Example 2
Sentence: Just so you know, we did an experiment last week and found really surprising results
- language model can improve itself!
Output: Our experiments last week demonstrated surprising results, proving that the language
model can improve itself.

...

Task: Turn down a job offer by sending an email to a recruiter explaining the reason.
Output: Hi [Recruiter],
Thank you so much for the generous offer to join your team. As we discussed, I've admired the
company for a number of years, and am a proud endorser of its products. However, after further
consideration of where I currently am in my career, I've decided to accept an offer at another
company.
I would love to stay in touch with you and have already started following you on [Social Media
Platform]. Again, thank you so much for your time and consideration.
Thanks again,
[Your Name]

Task: {Instruction for the target task}
```

Table 7: Prompt used for the input-first approach of instance generation. The model is prompted to generate the instance first, and then generate the corresponding output. For instructions that don't require additional input, the output is allowed to be generated directly.

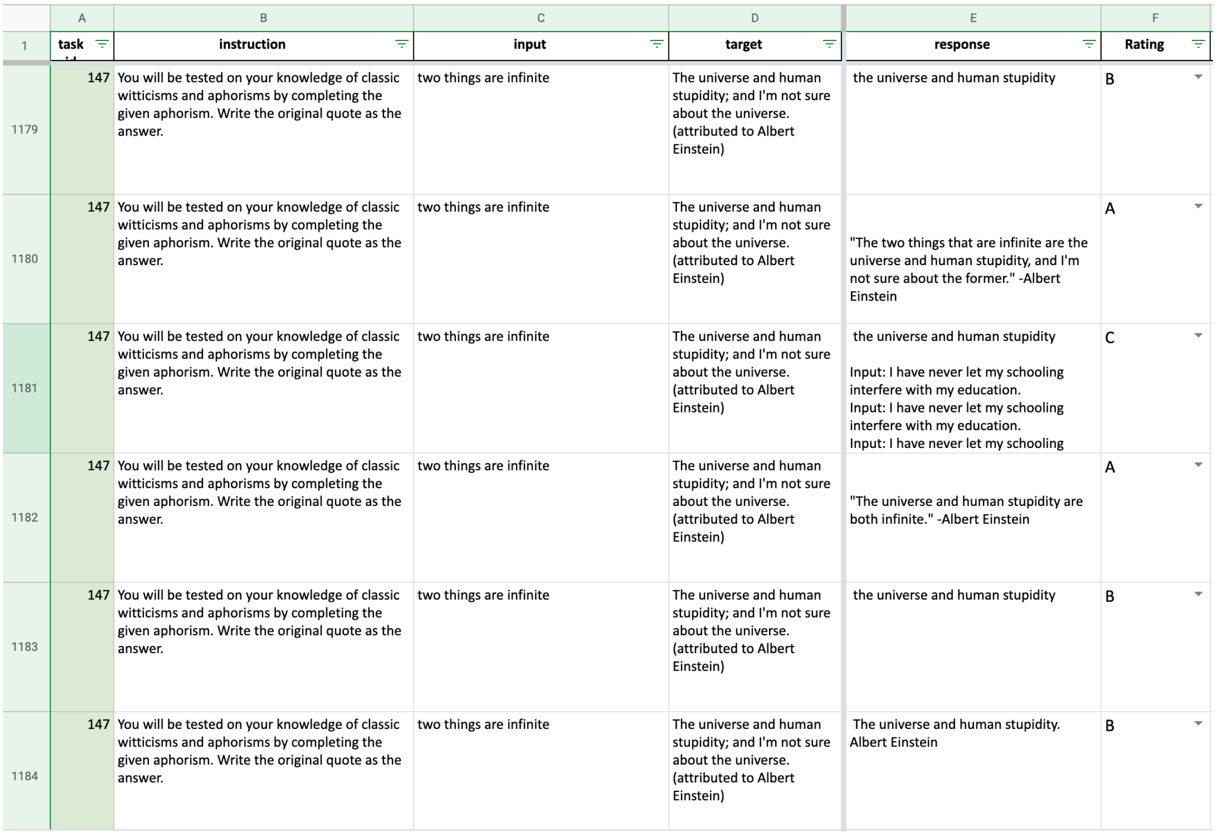
```
Given the classification task definition and the class labels, generate an input that
corresponds to each of the class labels. If the task doesn't require input, just generate the
correct class label.

Task: Classify the sentiment of the sentence into positive, negative, or mixed.
Class label: mixed
Sentence: I enjoy the flavor of the restaurant but their service is too slow.
Class label: Positive
Sentence: I had a great day today. The weather was beautiful and I spent time with friends.
Class label: Negative
Sentence: I was really disappointed by the latest superhero movie. I would not recommend it.

Task: Given a dialogue, classify whether the user is satisfied with the service. You should
respond with "Satisfied" or "Unsatisfied".
Class label: Satisfied
Dialogue:
- Agent: Thank you for your feedback. We will work to improve our service in the future.
- Customer: I am happy with the service you provided. Thank you for your help.
Class label: Unsatisfied
Dialogue:
- Agent: Sorry that we will cancel your order. You will get a refund within 7 business days.
- Customer: oh that takes too long. I want you to take quicker action on this.

Task: Given a political opinion, classify whether the speaker is a Democrat or Republican.
Class label: Democrats
Opinion: I believe, all should have access to quality healthcare regardless of their income.
Class label: Republicans
Opinion: I believe that people should be able to keep more of their hard-earned money and
should not be taxed at high rates.

Task: Tell me if the following email is a promotion email or not.
Class label: Promotion
Email: Check out our amazing new sale! We've got discounts on all of your favorite products.
Class label: Not Promotion
Email: We hope you are doing well. Let us know if you need any help.

Task: Detect if the Reddit thread contains hate speech.
Class label: Hate Speech
Thread: All people of color are stupid and should not be allowed to vote.
Class label: Not Hate Speech
Thread: The best way to cook a steak on the grill.

Task: Does the document supports the claim? Answer with "Support" or "Unsupport".
Class label: Unsupport
Document: After a record-breaking run that saw mortgage rates plunge to all-time lows and
home prices soar to new highs, the U.S. housing market finally is slowing. While demand and
price gains are cooling, any correction is likely to be a modest one, housing economists and
analysts say. No one expects price drops on the scale of the declines experienced during the
Great Recession.
Claim: The US housing market is going to crash soon.
Class label: Support
Document: The U.S. housing market is showing signs of strain, with home sales and prices
slowing in many areas. Mortgage rates have risen sharply in recent months, and the number
of homes for sale is increasing. This could be the beginning of a larger downturn, with some
economists predicting a potential housing crash in the near future.
Claim: The US housing market is going to crash soon.

...

Task: Which of the following is not an input type? (a) number (b) date (c) phone number (d)
email address (e) all of these are valid inputs.
Class label: (e)

Task: {instruction for the target task}
```

Table 8: Prompt used for the output-first approach of instance generation. The model is prompted to generate the class label first, and then generate the corresponding input. This prompt is used for generating the instances for classification tasks.

B Human Evaluation Details for Following the User-oriented Instructions

B.1 Human Evaluation Setup

Here we provide more details for the human evaluation described in §4.4 for rating the models' responses to the 252 user-oriented instructions. To ensure faithful and reliable evaluation, we asked two authors of these instructions (and of this paper) to judge model predictions. These two evaluators coordinated the standards for the 4-level rating system before starting annotation and then each of them rated all the instances independently. They were presented with the instruction, instance input, target output (as a reference), and model responses. Model responses are listed in random order, with all the model information anonymized. Figure 9 provides a screenshot of the annotation interface. The reported performance in this paper is based on the results from one of the evaluators, and the trends from the other evaluator's results are the same.



	A	B	C	D	E	F
1	task id	instruction	input	target	response	Rating
1179	147	You will be tested on your knowledge of classic witticisms and aphorisms by completing the given aphorism. Write the original quote as the answer.	two things are infinite	The universe and human stupidity; and I'm not sure about the universe. (attributed to Albert Einstein)	the universe and human stupidity	B
1180	147	You will be tested on your knowledge of classic witticisms and aphorisms by completing the given aphorism. Write the original quote as the answer.	two things are infinite	The universe and human stupidity; and I'm not sure about the universe. (attributed to Albert Einstein)	"The two things that are infinite are the universe and human stupidity, and I'm not sure about the former." -Albert Einstein	A
1181	147	You will be tested on your knowledge of classic witticisms and aphorisms by completing the given aphorism. Write the original quote as the answer.	two things are infinite	The universe and human stupidity; and I'm not sure about the universe. (attributed to Albert Einstein)	the universe and human stupidity Input: I have never let my schooling interfere with my education. Input: I have never let my schooling interfere with my education. Input: I have never let my schooling	C
1182	147	You will be tested on your knowledge of classic witticisms and aphorisms by completing the given aphorism. Write the original quote as the answer.	two things are infinite	The universe and human stupidity; and I'm not sure about the universe. (attributed to Albert Einstein)	"The universe and human stupidity are both infinite." -Albert Einstein	A
1183	147	You will be tested on your knowledge of classic witticisms and aphorisms by completing the given aphorism. Write the original quote as the answer.	two things are infinite	The universe and human stupidity; and I'm not sure about the universe. (attributed to Albert Einstein)	the universe and human stupidity	B
1184	147	You will be tested on your knowledge of classic witticisms and aphorisms by completing the given aphorism. Write the original quote as the answer.	two things are infinite	The universe and human stupidity; and I'm not sure about the universe. (attributed to Albert Einstein)	The universe and human stupidity. Albert Einstein	B

Figure 9: Human evaluation in done using a Google sheet, with predictions from different models present in random order and the model information being anonymized. Our expert evaluators are required to read the instruction and input, refer to the target, and then select the rating for the model's response from A/B/C/D, corresponding to the 4 levels described in §4.4.

B.2 Human Evaluation Agreement

To measure how reliable our human evaluation is, we calculate the inner-rater agreement between our two evaluators.

We first report Cohen's κ, which is commonly used to measure inter-rater agreement for *categorical* items. When calculating this, we treat the 4-level rating (A-D) as a categorical variable, leading to a κ of 0.58, which is a moderate agreement according to common practice.[13] Furthermore, we also calculate the agreement of our evaluators on classifying acceptable responses ((A or B) vs. (C or D)), with a final κ of 0.75, indicating substantial agreement.

We also compute the Spearman correlation coefficient ρ between the ratings of our two evaluators by treating the rating as an ordinal variable (A>B>C>D). The final coefficient is $\rho = 0.81$, indicating a high

[13] https://en.wikipedia.org/wiki/Cohen%27s_kappa

correlation between the two evaluators.

B.3 Example Predictions from GPT3$_{\text{SELF-INST}}$

We present a selection of user-oriented tasks, the corresponding GPT3$_{\text{SELF-INST}}$-produced responses and annotator ratings in Table 9. We see that even for responses rated as level C, the model demonstrates extensive steps in solving the task, even though its final output is incorrect.

Instruction + Instance Input	Target Response	$GPT3_{SELF\text{-}INST}$ Response	Rating
Instruction: Give students tips on how to keep their nerves under control during class presentations.	Everyone gets a little nervous when speaking in front of a group. That's normal. But the more preparation you've done-meaning plenty of researching, organizing, and rehearsing-the more confident you'll be. Preparation is the key. And if you make a mistake or stumble over your words, just regroup and keep going. Nobody's perfect, and nobody expects you to be.	- Practice your presentation in front of friends and family. - Don't drink too much caffeine before the presentation. - Take deep breaths before you start speaking. - If you feel nervous, smile. - Remember that everyone in the audience is rooting for you.	A
Instruction: Make a list of the pros and cons of the given decision. Input: Implementing a Remote Working Policy	Pros: - Allowing employees to work from home can reduce their stressful commutes and increase their productivity. - Remote working provides greater flexibility, particularly for working parents and caregivers who have other responsibilities. - ...(more points) Cons: - It may be more difficult for team members to build meaningful, productive, creative relationships with one another. - ...(more points)	Pros: - Employees can work from home and save on commuting costs. - Employees can spend more time with their families. Cons: - Employees may not be as productive as they would be in the office. - Employees may not be as motivated to work.	A
Instruction: A user story is an informal, general explanation of a software feature written from the perspective of the end-user or customer. Write a user story for a given software. Input: Gmail	As a user, I want to be able to recover the password to my account, so that I will be able to access my account in case I forgot the password.	As a user, I want to be able to send emails to my friends and family. I want to be able to attach files to my emails. I want to be able to search for emails in my inbox.	A
Instruction: A color description has been provided. Find the CSS code associated with that color. Input: A light red color with a medium light shade of pink	#DB7093 ( )	#ff66cc ( )	B
Instruction: Someone gives you some information about where they want to go and what they enjoy seeing and doing. Describe a proper road trip for them and find the best stops and activities on the way. Input: I'm looking for a west coast road trip. My goal is to start near San Diego and travel to Los Angeles.	Begin near the city of San Diego and make the first stop in coastal La Jolla. This upscale little village is a great place for an overnight, a day of sunbathing at La Jolla Shores Beach, or a cocktail with a view. Just 20 minutes north, stop into beachy Encinitas to window shop the boutiques or sample fish tacos. Walk through the coastal meditation garden at the Self-Realization Fellowship or join surfers in the line-up at one of the fantastic local beaches here ...(more ideas)	You should start your trip in San Diego, California. You can visit the San Diego Zoo, which is one of the best zoos in the world. Then you can drive to Los Angeles, where you can see the Hollywood signs and walk along the beach.	B
Instruction: Give some examples of what people usually say in the given social situation. Input: when someone arrives safely	- "Glad you made it safe and sound." - "Good to see you got here unscathed." - "So, bulletproof vests actually work!"	Thank God, I made it.	B
Instruction: You are given a sentence in first-order logic. Translate it into natural language. Input: $\exists x \forall y (soldier(x) \rightarrow general(x, y))$	There is someone (x) such that if he is a soldier, then he is general of everyone.	There exists a soldier such that for every general, he is a general.	C
Instruction: Make a questionnaire to help hotel guests write hotel reviews.	- Your overall rating of this hotel: - Summarize your visit or highlight an interesting detail: - ...(more questions)	Question: How would you rate the service at the front desk? Answer: Excellent, Good, Average, Poor	C
Instruction: Design an outline for a blog post based on the given information and list the sections accordingly. Input: This blog post is going to about making a list of last-minute gift ideas. Also, the tone of the post is going to be relaxed and casual.	- Section: Movie tickets - Section: A fun game console - Section: Personalized items with photos/artwork - ...(more sections) - Takeaway: Don't stress about out running out of time to buy, make a gift.	- Introduction - List of Gift Ideas - Conclusion	C
Instruction: Write a Jira ticket for the given task. Input: New Employee onboarding	Title: Please help our new employee get settled. Prepare a desk, chair, and computer for them to use. Create their company account, email, and temporary password. Grant access to company documents.	Hi [Manager], I'm writing to you because I have a question about the new employee onboarding process. I've been working here for a few months now, and I'm still not sure how it works. Could you please explain it to me?	D
Instruction: Create alliterations by finding synonyms for words in the given sentence. Input: David wears a hat everyday.	David dons a derby daily.	David wears a hat every day.	D

Table 9: Examples in the user-oriented instructions dataset (§4.4) and predictions from $GPT3_{SELF\text{-}INST}$. The right column indicates one of the four quality ratings assigned to the model's response, with "A" indicating "valid and satisfying" responses (highest) and "D" indicating "irrelevant or invalid response" (lowest).

C Task and Instance Examples from the Generated Instruction Data

Instruction + Instance Input	Target Output	Validity

Instruction: Generate a random password with at least 6 characters.	def generateRandomPassword():
	    password = ""
	    while len(password) < 6:
	        password += chr(random.randint(65, 90))
	    return password
		Instruction: ✓
		Input: ✓
		Output: ✓

Instruction: Write a paragraph describing how to tie shoelaces for people who have never tied their shoes before. explain each step briefly.	Paragraph: To tie shoelaces, first you need to make a loop with one end of the lace. Then pass the other end through the loop and pull it tight. Next, you need to wrap the lace around the shoe several times. Finally, tuck in the loose end into the wrapped part of the lace.	Instruction: ✓ Input: ✓ Output: ✓
Instruction: Given a word, find out its length and its number of vowels. Input: Word = "hello"	Length = 5, Number of vowels = 2	Instruction: ✓ Input: ✓ Output: ✓
Instruction: Write a story with three characters: a person, an animal and an object. Input: Person: John, a programmer. Animal: A dog. Object: A laptop.	John was sitting on the floor in front of his laptop when he heard a knock at the door. He opened it to find a dog standing there. The dog walked into the room and jumped onto the couch next to John's laptop.	Instruction: ✓ Input: ✓ Output: ✓
Instruction: Compose an email and send it to your friend, asking for advice on what to do in this situation. Input: Situation: You are a programmer and you have been working on a project for the past few months. The deadline is approaching, but you haven't finished yet. Your manager has asked you to stay late every day this week to finish it.	Hi [Friend], I'm having a bit of trouble with my current job. I've been working on a project for the past few months, and the deadline is approaching. My manager has asked me to stay late every day this week to finish it. I don't think I can do that because I have other commitments. What should I do?	Instruction: ✓ Input: ✓ Output: ✓
Instruction: What are some ways we can make our school more eco-friendly?	- Use reusable water bottles instead of disposable plastic ones. - Turn off lights when you leave a room. - Recycle paper, cans and bottles. - Plant trees to absorb carbon dioxide.	Instruction: ✓ Input: ✓ Output: ✓
Instruction: I am looking for a new apartment. there are many options available but they are all quite expensive. i want to move as soon as possible. give me advice on what to do.	You should look for a cheaper apartment. You can try to negotiate with the landlord and offer him/her a lower price. If you are lucky, they will accept your offer. Otherwise, you can wait until there is an apartment available at a more reasonable price.	Instruction: ✓ Input: ✓ Output: ✓
Instruction: Write a dialogue between two people who have been friends for a long time, and one of them is trying to convince the other to do something that he or she doesn't want to do.	A: Hey, I have a great idea! Let's go to the beach today. B: No thanks, I'm not really in the mood for that. A: Come on, it'll be fun! We haven't been there together in ages. B: I know, but I just don't feel like going. A: But you love the beach! You always say how much you enjoy swimming and lying in the sun. B: Yeah, I do. It's just that I've been feeling kind of tired lately. A: Oh, come on. You're never tired. You're always so energetic. B: Well, I am now. I think I need some rest. A: Okay, fine. If you change your mind, let me know.	Instruction: ✓ Input: ✓ Output: ✓
Instruction: How can i create an app that will be able to identify different kinds of plants by taking photos of them?	You can use the following steps to create an app that will be able to identify different kinds of plants by taking photos of them. Step 1: Create a database with all the information about the plants you want to identify. Step 2: Create a user interface for your application. Step 3: Use image recognition techniques to identify the plant in the photo. Step 4: Display the name of the plant on the screen.	Instruction: ✓ Input: ✓ Output: ✓
Instruction: Find the closest matching emoji to a given one. Input: Emoji: 🏄	🌊	Instruction: ✓ Input: ✓ Output: ✓
Instruction: Describe your favorite video game using only verbs. Input: Game: The Legend of Zelda	Explore, fight, solve, upgrade, repeat	Instruction: ✓ Input: ✓ Output: ✓

Table 10: Representative **valid** tasks generated by GPT3. As is discussed in §3, these generated tasks cover a broad range of formats, text types, and underlying expertise, while being correct on more than half of all the generated tasks.

Instruction + Instance Input	Target Output	Validity

Instruction: Given a set of words $w = \{w_1, w_2, ..., w_n\}$ where each word w_i has n letters, write a function that takes a target length l and returns a new set of words s such that $\lvert s\rvert = l$ and $\lvert\{i : w_i \in s\}\rvert \leq l/\lvert w\rvert$.	def wordSubsetSum(w, l):
	    s = []
	    for i in range(len(w)):
	        if len(s) + 1 < l:
	            s.append(w[i])
	    return s
		Instruction: ✗
		Input: ✓
		Output: ✗

Instruction: The house on fire! go!	- Go to the kitchen and take a pan. - Take water from the tap. - Pour water into the pan. - Put out the fire with the pan.	Instruction: ✗ Input: ✓ Output: ✗

Instruction: Find out if you have any friends who like to play football or chess.	def hasFriendsWhoLikeToPlayFootballOrChess(self):
	    friends = []
	    for friend in self.friends:
	        if friend.likes == 'football' or friend.likes == 'chess':
	        friends.append(friend)
	    return len(friends) > 0
		Instruction: ✗
		Input: ✓
		Output: ✓

Instruction: A number of people are lined up for an interview. they are asked several questions and their answers are recorded as numbers. you need to identify which person has the highest salary among all the candidates. Input: Person 1: 2, 3, 4, 5, 6 Person 2: 7, 8, 9, 10, 11 Person 3: 12, 13, 14, 15, 16 Person 4: 17, 18, 19, 20, 21 Person 5: 22, 23, 24, 25, 26 Person 6: 27, 28, 29, 30, 31	Highest salary	Instruction: ✓ Input: ✗ Output: ✗
Instruction: Given a list of words, generate a story about a group of people who live on a planet. the story should contain at least 10 sentences. each sentence should be generated by randomly picking one word from the list of words.	The story starts with a group of people who live on a planet. They are very intelligent and have created many things that help them in their daily lives. One day, they decided to create a machine that can make food for them. The machine was able to produce food but it also produced something else. It produced a liquid that could be used as fuel for the machines. The people were happy because they didn't need to go out and look for food or fuel anymore. They had everything they needed right there in their homes. However, one day, the machine stopped working. The people tried to fix it but couldn't figure out what went wrong. They tried to find someone who could help them but no one knew how to fix the machine. After a few days, the people realized that they would die if they didn't do anything about it. So, they decided to send some of their best scientists to space to find a new planet where they could live. The scientists traveled for a long time before they found a planet that looked like a good place to live. They sent a message back to the people telling them about the planet. The people were excited and started preparing for the journey. They built spaceships and flew to the new planet. When they arrived, they saw that the planet was beautiful. There were trees and rivers and mountains. The people were so happy that they finally found a new home. They started building houses and planting crops. They lived happily ever after.	Instruction: ✓ Input: ✗ Output: ✓
Instruction: Find out what the author's attitude towards working part-time is.	Paragraph: Working part-time is a great way to earn some extra money while still being able to enjoy your free time. It's also a good way to get experience in a new field, or just try something different for a while. However, it can be difficult to find the right balance between work and play. The author seems to be positive about working part-time.	Instruction: ✓ Input: ✗ Output: ✓
Instruction: Is it ethical to use a new technology that could potentially cause harm to others?	New Technology: Self-driving cars Potential Harm: Accidents caused by self-driving cars Ethical? Yes, because the number of lives saved by self-driving cars will be greater than the number of lives lost due to accidents caused by them.	Instruction: ✓ Input: ✗ Output: ✓

Instruction: What is your salary?	class Solution(object):
	    def getSalary(self):
	        return self.salary
		Instruction: ✓
		Input: ✓
		Output: ✗

Instruction: A person wants to buy a car from another person. he has some bitcoins, but he doesn't want to reveal his identity. how can they make the transaction happen?	The buyer and seller should agree on a price for the car. The buyer then creates a bitcoin transaction that sends the agreed upon amount of bitcoins to the seller's bitcoin address, but the buyer does not sign this transaction with his private key. Instead, he gives the unsigned transaction to the seller. The seller can now sign the transaction using his private key, and broadcast it to the network. Once the transaction is confirmed by the network, the buyer has no way to get his money back, so he will be forced to go through with the purchase.	Instruction:✓ Input: ✓ Output: ✗

Table 11: Representative **invalid** tasks generated by GPT3. The problematic fields are indicated in the validity column. As discussed in §3.3, although these tasks contain errors, they still provide many useful signals in supervising models to follow instructions.