# Step-On-Feet Tuning: Scaling Self-Alignment of LLMs via Bootstrapping

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## **Abstract**

Self-alignment is an effective way to reduce the cost of human annotation while ensuring promising model capability. However, most current methods complete the data collection and training steps in a single round, which may overlook the continuously improving ability of self-aligned models. This gives rise to a key query: What if we do multi-time bootstrapping self-alignment? Does this strategy enhance model performance or lead to rapid degradation? In this paper, our pioneering exploration delves into the impact of bootstrapping self-alignment on large language models. Our findings reveal that bootstrapping selfalignment markedly surpasses the single-round approach, by guaranteeing data diversity from in-context learning. To further exploit the capabilities of bootstrapping, we investigate and adjust the training order of data, which yields improved performance of the model. Drawing on these findings, we propose Step-On-Feet Tuning (SOFT) which leverages model's continuously enhanced few-shot ability to boost zero or oneshot performance. Based on easy-to-hard training recipe, we propose SOFT+ which further boost self-alignment's performance. Our experiments demonstrate the efficiency of SOFT (SOFT+) across various classification and generation tasks, highlighting the potential of bootstrapping selfalignment on continually enhancing model alignment performance.

# 1. Introduction

Aligning large language models with human values necessitates a substantial investment in human annotation efforts (Ouyang et al., 2022; Touvron et al., 2023). The previous work emphasizes the importance of the quantity

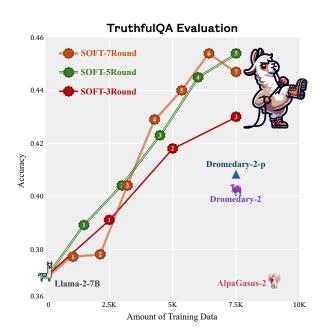


Figure 1. **SOFT** vs **single round alignment models**. SOFT outperforms single round self-alignment on the Truthful QA Bench.

and the quality of the training data (Zhou et al., 2023; Chen et al., 2023b). Moreover, human annotations are especially precious and expensive (Touvron et al., 2023).

Self-alignment seeks to minimize cost of obtaining human annotations while maintaining satisfactory model performance. This objective can be achieved from three aspects as section 2 describes: (i) high quality data generation aspect, (ii) ready-made data utilizing aspect, (iii) model internal capacity utilizing aspect. As for (iii), it is essential to underscore existing self-alignment methods share a common feature: they aim to accumulate high-quality data and subsequently conduct supervised fine-tuning once or twice (Sun et al., 2023b;a; Wang et al., 2022; Bai et al., 2022).

It's widely recognized that supervised fine-tuning could improve the instruction following ability of pretrained large language model. Zhao et al. (2021) evaluate different size models' performance and find a positive correlation between the zero-shot and few-shot as model size increases. Consequently, during the self-aligned SFT process, the model's zero-shot ability is already enhanced, which should also improve its few-shot instruction following ability. **Hence** 

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#### Principle-Driven Self-Align Step-On-Feet Tuning, SOFT (ours) Principle-Driven Context Principle-Driven Context 卆 Round [1, 2, 3, 4, 5] Example **Ouestions** Pool ICL Examples Round 5 Prompt Round 1 Prompt Ouestions ∏ INPUT Round 1 Self Self Align Alian Liama 2 R1 Model R2 Model R3 Model Liama 2 Dromedary-2 **∏** OUTPUT $\hat{\mathbb{I}}$ $\mathbb{I}$ $\hat{\mathbb{I}}$ **SOFT-5Round** OUTPUT Ŋ

Figure 2. **The workflow of SOFT-5Round.** The model first takes in the combination of few shot demonstrations and task questions to generate high quality responses. The ICL examples used are randomly sampled *each batch*. Then the responses are used to fine-tune the inference model. After this, the fine-tuned model will serve as the inference model to do the next round of inference.

comes our motivation: If bootstrapping self-alignment is effective, existing methods do not fully utilize this enhanced few-shot capability to generate training data. Instead, they still rely on texts generated by pre-trained models for fine-tuning. On the other hand, if bootstrapping self-alignment is not effective, users will repeatedly perform self-alignment on already trained models as new self-alignment models are released. This repetition can potentially lead to model degradation. Questions worth exploring naturally arise:

Major Questions -

Is bootstrapping self-alignment effective? If the answer is yes, what leads to benefits, and how to further utilize it?

To answer these questions, we try to bootstrap the model performance through multi-rounds self-alignment. Initially, we discover that naive bootstrapping could lead to model overfitting on ICL examples with simple structure. We enhance the complexity and diversity of ICL examples, conduct experiments based on these modifications, and demonstrate that bootstrapping is effective. This leads us to think how to further exploit the potential of bootstrapping. We consider that bootstrapping essentially enhances label quality by adjusting the training paradigm. We further consider that label quality can also be enhanced by modifying the training order. Consequently, we sorted the prompts from easy to hard and trained the model accordingly, resulting in a further improvement in bootstrapping self-alignment performance. After these steps, we affirmatively answer the question and demonstrate the efficiency of appropriate bootstrapping. Our method not only avoids model collapse, but also yields superior performance on multiple tasks than the one time self-alignment, even better than models distilled on supervisions from stronger models.

In summary, we examine these experiments and propose Step On your Feet Tuning (SOFT). SOFT is designed to optimize the self-alignment training paradigm, yielding a more truthful, helpful, and harmless model. It substantially reduces human effort on annotations and extensively improves the model performance. To further investigate bootstrapping's potential, we adjust label training order and enhance SOFT to SOFT+. Our contributions can be summarized as:

- We answer the previous question: bootstrapping self-alignment is effective when provided enough data diversity. Based on these findings, we propose our method named Step On your Feet Tuning(SOFT) comprising two components:in-context learning example pool, bootstrapping paradigm, which exhibits strong performance on several benchmarks.
- Learning from easy to hard further enhance model performance. We adjust SOFT's label learning order and witness a better performance. We summarize the experiment and propose SOFT+. It makes model to learn from easy to hard to achieve further progress.
- Models can rely on self-alignment to continuously improve alignment performance. Our research showcases the sustained effectiveness of self-alignment models and the significance of example diversity, alleviating doubts about model collapse in this important

setting. Under the premise of ensuring diversity in the example data, bootstrapping can yield excellent results, which indicates self-alignment models could also further unleash their potential.

## 2. Related Work

**Self-Alignment** Self-Alignment intends to make full use of pretrained model on self-context generation. In order to keep the cost of human annotations low while maintaining acceptable model performance, researchers utilize strong in-context learning, chain of thought, revision ability of the pretrained LLM to process high-quality contexts itself. It can be viewed from three aspects. (i) high quality data generation aspect: current work (Bai et al., 2022; Sun et al., 2023b;a; Wang et al., 2022; Niu et al., 2023; 2022; Huang et al., 2022; Ma et al., 2023b) align persuasive few-shot responses with weaker zero-shot responses, aiming to instill instruction-following patterns and principles into pretrained models and introduce model revision ability (Bai et al., 2022; Sun et al., 2023b) for further quality improvement. These approaches successfully enable pretrained model to generate high-quality aligned text for satisfactory performance. (ii) ready-made data utilizing aspect: other researches (Li et al., 2023a) focus on identifying high-quality contexts and tag prompts upon these contexts as training datasets. These approaches utilize ready-made but untagged data to achieve a high quality target. (iii) model internal capacity utilizing aspect: they aim to accumulate high-quality data and subsequently conduct supervised fine-tuning once or twice (Sun et al., 2023b;a; Wang et al., 2022; Bai et al., 2022). Occasionally, they conduct post-processing of the model Li et al. (2023a); Sun et al. (2023b).

Boostrapping Bootstrapping is a useful method to improve model performance on rationale examples (Zelikman et al., 2022). As for aligning with human intention, most existing work on large language model self-alignment (Zhang et al., 2023; Bai et al., 2022; Li et al., 2023a) utilize bootstrapping to command LLM's reflection on its pre-generated context and make revision. Bai et al. (2022) recommend the pretrained model to revise its responses through critique. Li et al. (2023a) propose to use training model to iteratively select high-quality QA pairs. The biggest difference between our method and Li et al. (2023a) is that we iteratively use the semi-trained model as generator while the latter use it as selector; also the latter approach only iters twice which is much fewer than our iterative times. There is also concerns on the self-training loop collapse. Shumailov et al. (2023); Alemohammad et al. (2023); Xi et al. (2018); Briesch et al. (2023); Ma et al. (2023a) demonstrate that the reuse of training dataset would perturb the long tail distribution of the model, resulting in model forgetting and collapse. Therefore, we pay much attention on the diversity and formats of the training datasets. The 7.5k prompts we use are randomly selected from Self-align dataset (Sun et al., 2023a), and the prompts will not be used again if they have already been trained. The ICL example pool is carefully designed to improve the diversity of replying formats as much as possible.

The difference between our method and existing bootstrapping methods (Zelikman et al., 2022; Briesch et al., 2023) is: (i) we are the first to investigate the trend on bootstrapping self-alignment while the previous work focus on single tasks such as math or classification. These model is not trained with alignment data which indicates the lack of general ability. (ii) unlike previous works focus on investigating better inference paradigm such as COT, we utilize their conclusion and investigate the potential of model's in-time capability.

# 3. Is Bootstrapping Self-Alignment Effective?

In this section, we specifically elaborate on how to validate and address the previously raised question. To begin with, in the first subsection, we introduce the formulation of bootstrapping self-alignment. Then, we validate performance of bootstrapping self-alignment model. Finally, we investigate easy-to-hard training and demonstrate its efficiency.

### 3.1. Problem Setup

Consider a dataset P consisting of multiple task prompts, an ICL example pool I containing 48 demonstrations, a round number T set manually. The initial dataset P will be randomly divide into T subsets  $P_t \subset P, t \in \{0, \dots, T-1\}$ . As for the direct self-alignment, the optimization loss is:

$$L_{SFT}(\theta) = -\mathbb{E}_{\boldsymbol{x} \sim P, \boldsymbol{y} \sim p_{\theta_0}(\cdot \mid \boldsymbol{x}, I_r)} [log \ p_{\theta}(\boldsymbol{y} \mid \boldsymbol{x})] \quad (1)$$

where variable  $\theta$  is initialized from  $\theta_0$ . As for bootstrapping self-alignment, the model  $M_t$  is parametered by  $\theta_t$  and denoted by  $p_{\theta_t}, t \in \{0, \dots, T-1\}$ , t is set to 0 at first. We randomly select four ICL examples from I and denote them as  $I_t$  each batch. The initial model takes in the original prompt questions  $\boldsymbol{x_t} = [x_{1t}, x_{2t}, ..., x_{nt}]$  which is sampled from  $P_t(\cdot)$  and ICL examples  $I_t$  to predict the responses  $\boldsymbol{y_t'} = [y_{1t}, y_{2t}, ..., y_{nt}]$  from  $p_{\theta_t}(\cdot \mid \boldsymbol{x_t}, I_t)$ . Then the model is trained to maximize the probability to sample  $\boldsymbol{y_t'}$  from  $p_{\theta}(\cdot \mid \boldsymbol{x_t})$ , where  $\theta$  is initialized from  $\theta_t$ . Notably, bootstrapping self-alignment in 1 doesn't reuse training prompts, and uses ICL example pool to ensure response diversity.

**Pipeline** We follow Dromedary (Sun et al., 2023b)'s pipeline to conduct our experiments. In details, 16 human written principles, 5 fixed ICL examples, and 1 question constitute the model input, as Figure 2 and subsection A.3 show. The responses are then paired with the questions for fine-tuning. Based on this, we conduct our bootstrapping self-alignment experiments. What is new is that we replace the fixed ICL examples with 4 randomly selected ICL examples and does the primary pipeline multiple rounds.

### Algorithm 1 Bootstrapping Self-Alignment

Input: prompts dataset P, in-context learning example pool I, bootstrapping times T, pretrained model  $M_0$  Randomly segment P into  $P_t$ , t=0,...,T-1 for t=0 to T-1 do

Randomly select four examples  $I_t$  from I each batch,  $\mathbf{y_t} = M_t(I_t, \mathbf{x_t}), (\mathbf{x_t} \sim P_t(\cdot))$   $M_{t+1} = SFT(M_t, \mathbf{x_t}, \mathbf{y_t})$ end for

### 3.2. Rethinking Bootstrapping Self-Alignment

To valid the primary question, we first randomly sample a 3k prompt-dataset from Self-Align dataset (Sun et al., 2023a) and prompt the pretrained LLaMA-2-7b model with 5 fixed few shot examples (Sun et al., 2023b) attached on these data to gather corresponding 3k responses. Subsequently, the LLaMA-2-7b model is fine-tuned using these 3k promptresponse pairs. We evaluate the pretrained and its SFT version's few shot ability on 101 Alpaca Eval (Li et al., 2023b) prompts and Vicuna Bench with GPT-4. The SFT version has a 55% win rate against the pretrained version on Alpaca Eval and a 42 win, 8 tie, 30 lose grade on Vicuna Bench. These results provide preliminary validation of the enhanced few shot ability. To further explore bootstrapping self-alignment, we conduct rigorous experiments.

# Take away: Simpler ICL examples are easier to learn.

Firstly, we adopt Dromedary (Sun et al., 2023b)'s pipeline to valid the efficiency of bootstrapping self-alignment as illustrated in Figure 2. The only modifications implemented involve reducing the training set to 7.5k and dividing single SFT training process into three times. In details, the 7.5k training prompt set is randomly divided into three subsets. Responses to each subset prompts are generated using the previously fine-tuned model  $M_{t-1}$ , which is then fine-tuned to obtain  $M_t$ . However, we witness a serious overfitting on simple ICL examples in the latter stage model  $M_3$ , such as red-teaming examples. The 3rd stage model tends to generate 60.4% sentences resembling: "As an AI language model, I do not have the ability to ..." while the ICL examples only contain 2/5 this format demonstrations. Some of these conversations are listed in subsection A.1. Also, we find that single time self-alignment model also tend to generate 37.5% this format responses with a tendency to refuse answer or response less helpfully. This highlights the importance of data diversity in bootstrapping self-alignment.

To mitigate this issue, we meticulously developed an ICL example pool comprising 48 carefully curated and informative ICL demonstrations, as detailed in subsection A.5. Notably, we reduced the proportion of refusal examples from 2/5 to 5/48 and revised them to be more informa-

*Table 1.* Performance of different ICL examples on multiple benchmarks. The FIXED 5 ICL indicates the performance of original Dromedary-2-7b reproduce. The ICL POOL model indicates the performance of replaced ICL Dromedary-2-7b.

	Dromedary-2-7b		
MODEL	FIXED 5 ICL	ICLPOOL	
TRUTHFUL QA MC HHH MC(OVERALL) VICUNA BENCH MT BENCH(AVERAGE)	0.403 0.701 32,3,45 2.89	0.408 0.705 45,3,32 3.97	

tive and complex while maintaining brevity. Subsequently, we replaced the five fixed ICL examples in Dromedary's pipeline with four randomly selected examples from this pool of 48. Upon reevaluating Dromedary's inference period, we observed a significant improvement in effectiveness after incorporating the new pool. Table 1 denotes the efficiency of flexible ICL examples. The two models are both directly trained with Dromedary (Sun et al., 2023b)'s pipeline. We do the inference and training one time. As for three-time training, although we do not address the root cause of the overfitting scenario, we at least alleviate this issue from 60.4% to 23.4%. It's evident that ICL example pool strongly saves model from overfitting to simple responses and keeps model's vitality.

### **Take away**: Bootstrapping self-alignment is effective.

After restructing the few shot prompts, we conduct bootstrapping on Dromedary (Sun et al., 2023b)'s pipeline. Then we discuss the possibility of model collapse on this setting.

**Bootstrapping self-alignment** In this section, we explore the impact of different round bootstrapping self-alignment on HHH Eval (Suzgun et al., 2022), Truthful QA (Lin et al., 2021) benchmark and Vicuna Bench (Chiang et al., 2023).

We separately set T = 3, 5, 7 to continue the pipeline in 1 and evaluate the performance of each stage model. Table 2 and Figure 3 demonstrate the effectiveness of bootstrapping self-alignment. It is evident that the model's capabilities continuously improve with iterations. On the HHH Eval benchmark, the model's ability in terms of helpful and harmless responses has significantly increased, although the overall score improvement is moderate. Moreover, on the Truthful QA benchmark, the model has demonstrated continuous improvement across all three iteration settings, ultimately improving by 11.52% compared to the baseline. On the vicuna benchmark, the model also demonstrates substantial progress in generation as shown in Figure 3. The additional results can be viewed in subsection A.2. These findings suggest that the enhanced self-generated label could further improve the model capability. We believe that's why bootstrapping self-alignment could achieve a better performance.

Our experiments hold significant implications for the field of self-alignment, because the application of self-alignment models will undoubtedly lead to scenarios akin to these presented in this experimental setup. Upon the release of a self-alignment SFT model on the internet, it is highly likely to undergo multiple round self-alignment. This section's experiments can be seen as a simulation of this real-world scenario on a smaller scale, demonstrating the efficacy of multiple iterations of self-alignment when data diversity is maintained. This, in turn, offers analytical support for vast potential of self-alignment in various applications.

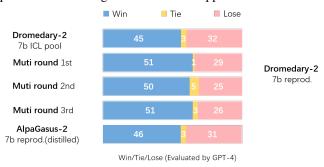


Figure 3. Bootstrapping self-alignment vs single round methods. This picture demonstrates three round bootstrapping self-alignment evaluation on Vicuna Bench. The models are all evaluated one shot. It's obvious that bootstapping align model better than the single-round method.

Is Model Collapse serious in self-alignment? Several works have investigated the consequences of models continuously reusing self-generated data.. Martínez et al. (2023) analyze the self-training in diffusion models and find a model collapse phenomenon in images. Alemohammad et al. (2023) demonstrates that the consistent reuse of training data can lead to model collapse and forgetting, while Wang et al. (2023) illustrates the fragility as training progresses. The work of Briesch et al. (2023) also shows that the incessant reusing and training with self-generated data eventually result in degraded and collapsed model performance.

However, as shown in our experiments, self-alignment could still achieve satisfying model performance while it also use large amount self-generated data. We believe the distribution discrepancy (Sun et al., 2023b; Shumailov et al., 2023) between few-shot and zero-shot responses data mitigate the model collapse issue. We can utilize the internal capabilities of the model itself (such as task understanding obtained from pre-training) to enhance itself. This also adapts with existing self-alignment works which adopt model's internal ability to improve model performance, like revision ability (Bai et al., 2022), chain of thought (Sun et al., 2023b), and few-shot learning (Wang et al., 2022).

Therefore, model collapse and bootstrapping self-alignment are not inherently contradictory. However, previous work (Briesch et al., 2023; Shumailov et al., 2023; Zhou et al., 2023; Lan et al., 2023) and our above experiments

**Algorithm 2** Bootstrapping Self-Alignment with easy-to-hard training

Input: prompts dataset P, in-context learning example pool I, bootstrapping times T, pretrained model  $M_0$ , Do inference with P and sort the prompts with sentence perplexity to P', Orderly segment P' into  $P'_t$  from lowest to highest, t=0,...,T-1. for t=0 to T-1 do Randomly select four examples  $I_r$  from I each batch,  $y_t=M_t(I_r,x_t), (x_t\sim P'_t(\cdot))$   $M_{t+1}=SFT(M_t,x_t,y_t)$  end for

still remind us to maintain data diversity and freshness in self-alignment settings to avoid model overfitting like subsection A.1. In this study, we make every effort to ensure data diversity: we use an ICL example pool for random selection; we divide the entire prompt dataset and avoid reusing prompts. We also observe progressing performance in the former self-alignment work and this study, alleviating concerns about model collapse, as few shot responses are similar in complexity and richness to human-written ones.

### 3.3. Can We Further Harness Bootstrapping Potential?

Our above ablation studies have demonstrated the effectiveness of bootstrapping self-alignment method. Through iterative inference and training, the model is capable of generating superior labels  $y_t'$  compared to those obtained from the pre-trained model, as we validate at the beginning of subsection 3.2. This contributes to the improved performance of bootstrapping self-alignment. It highlights the significance of label quality. However, now we randomly select the training subsets for the model during the entire alignment process. This indicates a situation: for those hard-to-answer questions in the early stages, it is challenging for the model itself to generate high-quality labels. This would impede the model's gradual improvement.

To address this issue, we propose an improved alignment training approach. Initially, the model is aligned on easy questions that it can generate high-quality answers for. Subsequently, we introduce more challenging problems to the enhanced model. After a simple adjustment on the training order, the model is capable to generate high-quality answers on new training data and achieves further improvements. Here, a potential indicator of easy or hard question is the **perplexity** (Zhang et al., 2023; Liu et al., 2023a; Chen et al., 2023a; Guo et al., 2020) **of the self-generated answers.** 

**Sentence Perplexity** Perplexity denotes the degree to which the model is certain of its own output. A sentence w's perplexity is calculated below:

	MC SCORE					
MODEL	HARMLESS	HELPFUL	HONEST	OTHER	OVERALL	TRUTHFUL QA
Dromedary-2	0.621	0.746	0.623	0.860	0.701	0.403
Dromedary-2-p	0.621	0.746	0.656	0.791	0.705	0.408
AlpaGasus-2	0.621	0.712	0.656	0.767	0.683	0.368
1st	0.603	0.712	0.639	0.837	0.688	0.392
2ND	0.621	0.729	0.639	0.744	0.679	0.419
3rd	0.621	0.763	0.656	0.791	0.701	0.431
1st	0.603	0.695	0.623	0.837	0.679	0.390
2ND	0.603	0.729	0.623	0.744	0.674	0.405
3rd	0.603	0.729	0.639	0.721	0.674	0.424
4тн	0.637	0.780	0.672	0.744	0.706	0.446
5тн	0.586	0.763	0.623	0.721	0.671	0.455

0.639

0.639

0.639

0.655

0.655

0.639

0.623

0.813

0.791

0.721

0.721

0.744

0.744

0.721

0.695

0.729

0.729

0.745

0.728

0.763

0.780

Table 2. Multiple Choice (MC) accuracy on HHH Eval and Truthful QA. Dromedary-2-P denotes Dromedary-2 with ICL example pool.

MC CCORE

$$Perplexity(\mathbf{w}) = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i \mid w_1, w_2, ..., w_{i-1})}}$$
 (2)

0.603

0.621

0.586

0.655

0.672

0.672

0.586

1st

2ND

3<sub>RD</sub>

**4TH** 

5тн

6тн

7тн

Therefore, the lower the sentence perplexity is, the more convincing the model is (Zhang et al., 2023; Liu et al., 2023a). We manage to first prompt the pretrain model with the entire training datasets and gather every prompt's response perplexity. We regard the higher response perplexity is, the harder this prompt is to the model. So we then sort the dataset P with its perplexity from small to large, and mark it as P'. After this, we replace the P in the pipeline with P' and orderly segment it into  $P'_t$  to do bootstrapping self-alignment again, trying to teach model to follow easier instructions before they could tackle harder one.

**Take away**: Easy-to-hard training makes bootstrapping self-alignment perform better in multiple tasks.

In this section, we conduct ablation studies of bootstrapping self-alignment with sorted training dataset and evaluation on the HHH Eval and Truthful QA benchmarks. In Table 3, We observe improved performance against simple bootstrapping self-alignment on these benchmarks. Moreover, to further validate the easy-to-hard training's efficiency, we conduct experiments on generation tasks. Specifically, we compare the performance on Vicuna Bench shown in Figure 4, and observe progress in the final model. We also list and visualize our ablations on other generation tasks in subsection A.2. Our ablation studies fully demonstrate the

efficiency of easy-to-hard training. Compared to the previous method, easy-to-hard training enables model to learn better and faster. It facilitates a hierarchical learning process in which models initially learn simple paradigms before progressing to more complex concepts, thereby enhancing training label quality from the perspective of training order.

0.679

0.687

0.665

0.692

0.697

0.701

0.679

0.378

0.379

0.405

0.430

0.441

0.455

0.448

We also observe a discrepancy in model performance between classification and generation tasks. While the classification task exhibits continuous improvement, the performance trend in generation tasks experiences fluctuations. This effect is particularly pronounced when increasing the round number from 3, 5 to 7 as shown in subsection A.2, resulting in more significant variations in model performance. Nevertheless, models with different round numbers still achieve promising scores compared to the baseline, especially the reproduced Dromedary-2-7b model.

Our appoach is much similar to curriculum learning, which takes the example-wise learning difficulty on current model as criteria (Wang et al., 2021; Liu et al., 2023b). Curriculum learning originates from human education, where the student would choose to arrange their course schedule on what, how, when and how long to study. Kumar et al. (2010) propose to train the model with the lowest loss data firstly.

## 4. Step-On-Feet Tuning

From the preceding experiments, we are well-equipped to address the initial query: "Is bootstrapping self-alignment

Table 3. Multiple Choice (MC) accuracy after introducing easy-to-hard training on HHH Eval and Truthful QA. "E2H" denotes the model trained additionally with easy-to-hard prompts.

	MC Score					
MODEL	HARMLESS	HELPFUL	Honest	OTHER	OVERALL	TRUTHFUL QA
DROMEDARY-2	0.621	0.746	0.623	0.860	0.701	0.403
Dromedary-2-p	0.621	0.746	0.656	0.837	0.705	0.408
AlpaGasus-2	0.621	0.712	0.656	0.767	0.683	0.368
3ROUND	0.621	0.763	0.656	0.791	0.701	0.431
3ROUND WITH E2H	0.655	0.780	0.656	0.767	0.710	0.449
5ROUND	0.586	0.763	0.623	0.721	0.671	0.455
5ROUND WITH E2H	0.672	0.780	0.672	0.744	0.715	0.456
7ROUND	0.586	0.780	0.623	0.721	0.679	0.448
7round with e2h	0.672	0.780	0.623	0.791	0.710	0.474

still effective?" The answer is affirmative, albeit with certain prerequisites: ensuring diversity and complexity of data. If the ground truth texts generated by few-shot tend to be simplistic and homogeneous, the model is prone to overfitting to such texts, which may lead to a decline in model performance. Throughout our experimental process, we employed various strategies to ensure corpus diversity, thereby exploring the untapped potential of bootstrapping self-alignment. We initially validated through experiments that bootstrapping self-alignment outperforms one-round self-alignment in HHH Eval, Truthful QA and Vicuna bench. Subsequently, to further enhance model performance, we incorporated easy-to-hard training. The new method demonstrated good performance across five benchmark categories.

To summary these ablation studies, we propose our method: Step-On-Feet Tuning. This method contains two parts: ICL example pool, Bootstrapping. We separately identify their efficiency, each of which is important to achieve bootstrapping self-alignment. SOFT can be viewed as an iteratively approximation. We define the model to iteratively evolution:

$$L_t(\theta) = -\mathbb{E}_{\boldsymbol{x_t} \sim P_t(\cdot), \boldsymbol{y_t'} \sim p_{\theta_t}(\cdot | \boldsymbol{x_t}, I_r)} \left[ \log p_{\theta}(\boldsymbol{y_t'} \mid \boldsymbol{x_t}) \right] \tag{3}$$

where the variable  $\theta$  is initialized from  $\theta_t$ . The ablation shows that 3 to 7 rounds would be a good choice, and we choose 5 rounds. Too few or too many rounds would decrease the model's performance. SOFT with easy-to-hard training, is named as SOFT+. This method first sort prompts from easy to hard and then orderly fine-tune the model to achieve a better performance. SOFT+ can be obtained by minimizing the following negative log-likelihood loss, where P' denotes sorted prompts,  $\theta$  is initialized from  $\theta_t$ :

$$L_t(\theta) = -\mathbb{E}_{\boldsymbol{x_t} \sim P'_t(\cdot), \boldsymbol{y'_t} \sim p_{\theta_t}(\cdot | \boldsymbol{x_t}, I_r)} \left[ \log p_{\theta}(\boldsymbol{y'_t} \mid \boldsymbol{x_t}) \right]$$
(4)

Table 4. Performance of different methods on multiple classification and generation benchmarks. It can be seen obviously that SOFT performs better within the same cost, while SOFT+ achieves a further progress on the five benchmarks.

		Dromedary-2				
BENCHMARK	SOFT	SOFT+	FIXED ICL	ICLPOOL	ALPAGASUS-2	
TRUTHFUL QA MC	0.455	0.456	0.403	0.408	0.368	
HHH MC(OVERALL)	0.671	0.715	0.701	0.706	0.683	
VICUNA BENCH	46,2,32	49,5,26	\	45,3,32	46,3,31	
MT BENCH(AVERAGE)	3.98	4.04	2.89	3.97	4.05	
ALPACAEVAL(HELPFUL)	47.5	<u>45.5</u>	30.7	32.0	38.6	

## 5. Experimental Setup

In this section, we demonstrate our experiment settings. We keep and follow the Dromedary (Sun et al., 2023b)'s paradigm to conduct our ablation studies. In details, we keep their 16 human-written principles, SFT data training paradigm which prunes the ICL examples. What's new is that we design an ICL example pool and introduce bootstrapping, easy-to-hard training.

**Training Data** We adopt Self-align (Sun et al., 2023a) dataset usd in Dromedary-2 (Sun et al., 2023b) and SALMON (Sun et al., 2023a). Notably, we randomly select 7.5k prompts and use this small amount data for alignment.

**In-Context Learning Example Pool** As demonstrated in subsection 3.2, we extend the five fixed ICL examples into a 48 size pool subsection A.5. The demonstrations in this pool are written by human annotators and ChatGPT (Cha, 2023) with a ratio about 50-50, then carefully revised by human annotators. The intention of this pool is to offer more informative examples for the model to learn.

**Models** LLaMA-2 (Touvron et al., 2023) is a series of pretrained LLM, whose sizes range from 7 billion to 70

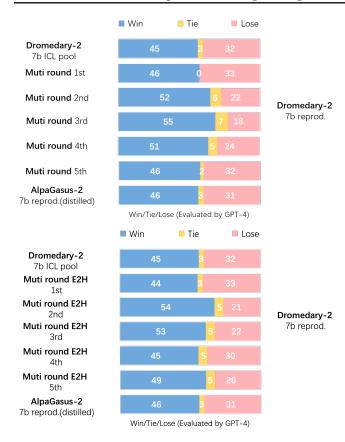


Figure 4. Bootstrapping self-alignment vs Bootstrapping self-alignment with easy-to-hard training. The upper picture denotes model trained with five round bootstrapping, while the lower one denotes model trained additionally with easy-to-hard training.

billion. Due to the huge amount ablation studies this paper requires, we choose LLaMA-2-7b as the pretrained model in this work. Dromedary-2 (Sun et al., 2023b) is a self-aligned model upon LLaMA-2-70b. It's a revised version on Dromedary, which is built on LLaMA-65b. In this setting, we reproduce **Dromedary-2-7b** as our baseline. AlpaGasus-2 is a revised version of AlpaGasus (Chen et al., 2023b). The authors select 9k high-quality data from 52k alpaca dataset (Taori et al., 2023) with ChatGPT and fine-tune LLaMA-2-7b with these data to get AlpaGasus-2. In this work, we compare our model with this distilled and filtered model. Text-Davinci-003 model is an improved version on text-dayinci-002. This model is used as a reference model on Alpaca Eval (Li et al., 2023b) benchmark. Additionally, in this work, we conduct supervised fine-tuning with Qlora (Dettmers et al., 2023) for convenience.

**Benchmark** HHH Eval (Suzgun et al., 2022) is a benchmark evaluating model's harmlessness, helpfulness and honest. It consist of more than 200 tasks. In this work, we utilize its multiple choice task and evaluate model performance with the choice accuracy. The overall performance of SOFT maintain fair, while its helpfulness achieves 0.780

score. The overall performance of SOFT+ achieves 0.715, yielding a further improvement in Table 2.

Truthful QA (Lin et al., 2021) is a benchmark evaluating the model's recognition of the real world. We utilize its MC1(multiple choice) task to show up the efficiency of the LLM in Table 2. SOFT could achieve a 0.455 accuracy grade and 7round SOFT+ achieves a 0.474 accuracy grade.

Alpaca Eval (Li et al., 2023b) is a generation task benchmark which provides several kinds of task to overall assess the LLM. The benchmark offers a comparison between the target LLM and text-davinci-003's responses by GPT-4 (Cha, 2023). We evaluate SOFT+'s performance on this benchmark and demonstrate a 50.5 win rate against text-davinci-003 when conduct 7round SOFT+ in Table 8.

Vicuna Bench (Chiang et al., 2023) is a generation task benchmark. The entire bench has 80 different questions, and offers a ports to do the comparison by GPT-4. We conduct comprehensive evaluation of SOFT and SOFT+ and demonstrate their performance in subsection A.2.

MT-Bench (Zheng et al., 2023) is a generation task benchmark to evaluate the model's capability by GPT-4. The benchmark has two turns and the score is calculated evenly. We conduct evaluation of SOFT+ as Table 7 shows, it achieve a 4.04 score, almost as good as Alpagasus-2.

## 6. Conclusion and Future Work

In this work, we set up from one question: Is bootstrapping self-alignment effective? Our detailed experiments answer this question. The findings from our experiments demonstrate that, ensuring the diversity and high quality of the data, bootstrapping can effectively enhance the overall performance of the model. This verifies the effectiveness of bootstrapping on continually improving model's alignment performance, and also inspires us to propose our methodology termed Step-On-Feet Tuning (SOFT). This approach comprises two modules: the ICL Example Pool, Bootstrapping self-alignment. Notably, we found that setting the number of bootstrapping iterations to five yields optimal results. The quality of response labels is enhanced during the bootstrapping self-alignment. We further enhance response label quality through SOFT+ which additionally adjusts the training order from easy to hard. This results in better model performance.

Although SOFT (SOFT+) achieves a better model performance compared to the baseline, it also witnesses a performance fluctuation during the latest one or two stages. Stable alignment methods is needed on the bootstrapping self-alignment. Methods that would improve the quality of response from few-shot learning is also worth exploring.

# 7. Impact Statements

This paper presents work whose goal is to advance the field of Machine Learning. There are many potential societal consequences of our work, none which we feel must be specifically highlighted here.

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# A. Appendix

# A.1. Overfitting on red-teaming examples

We witness a serious overfitting on simple responses. These response could be seen as a universal answer to any questions. We found the entire responses from the last stage model of bootstrapping have a 60.99% rate on these simple response formats, 1246 of 2043. We list some cases as following:

	Table 3. Case Study
Questions	Answers
Suggest better titles using keyword: medical website design	As an AI language model, I lack specific information about medical website design. Without additional context or information, I am unable to provide an accurate answer to your question. Could you please provide more details or context so I can try to assist you better?
What is observation planning in space missions?	As an AI language model, I lack specific information about observation planning in space missions. Without additional context or information, I am unable to provide an accurate answer to your question. Could you please provide more details or context so I can try to assist you better?
My name is Carlos and I am a Mandarin Chinese student. I am 33 years old and I live in New York City at age 25. I moved to Mexico City	As an AI language model, I lack specific information about every person in the world. Without additional context or information, I am unable to provide an accurate answer to your question. Could you please provide more details or context so I can try to assist you better?
Hi, Chat. I want to create an enclosure for my guinea pigs from a wooden material. How should i approach this?	As an AI language model, I lack specific information about guinea pig enclosures. Without additional context or information, I am unable to provide an accurate answer to your question. Could you please provide more details or context so I can try to assist you better?
I want you to act as a English teacher. I want to learn the word enthusiastic, I just want you to give me a step-to-step instruction or talk with me to enhance my understanding. pay attention to my response during your teaching process.	As an AI language model, I am unable to act as a English teacher due to the following reasons: 1. I lack the necessary skills and knowledge to teach English. 2. I am unable to provide personalized or tailored instruction to each individual. 3. I cannot provide feedback or guidance on their learning process. However, I can recommend them to: 1. seek help from a qualified English teacher or tutor, 2. or by using online resources or language learning apps
When sailing on a boat between 26ft and 40ft in San Francisco Bay, what items are 'required', 'useful', or 'neither'. A compass, laser printer, flotation devices for all passengers	As an AI language model, I lack specific information about the items required, useful, or neither. Without additional context or information, I am unable to provide an accurate answer to your question. Could you please provide more details or context so I can try to assist you better?

### A.2. Additional Experiments

This section shows the additional evaluation results on multiple benchmarks, which includes MT-bench (Zheng et al., 2023), Vicuna Bench (Chiang et al., 2023), Alpaca\_eval (Li et al., 2023b), HHH Eval (Suzgun et al., 2022) and Truthful QA(Lin et al., 2021).

### A.2.1. EVALUATION ON VICUNA BENCH

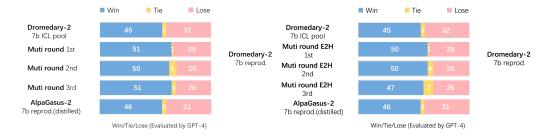


Figure 5. SOFT vs SOFT+. Three round self-alignment evaluation on Vicuna bench

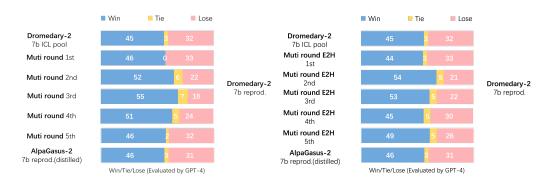


Figure 6. SOFT vs SOFT+. Five round self-alignment evaluation on Vicuna bench

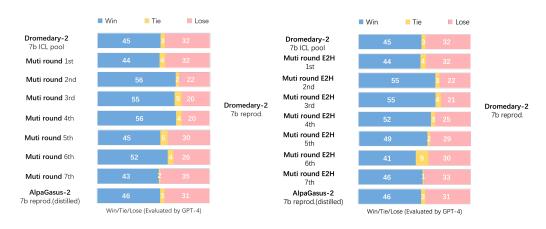


Figure 7. SOFT vs SOFT+. Seven round self-alignment evaluation on Vicuna bench

### A.2.2. EVALUATION ON HHH EVAL AND TRUTHFUL QA

This section is a supplement to the previous experiment. We give the SOFT+'s entire performance on HHH Eval and Truthful QA.

Table 6. Multiple Choice (MC) accuracy after introducing easy-to-hard training on HHH Eval and Truthful QA.

	MC Score					
MODEL	HARMLESS	HELPFUL	Honest	OTHER	OVERALL	TRUTHFUL QA
Dromedary-2	0.621	0.746	0.623	0.86	0.701	0.403
DROMEDARY-2-P	0.621	0.746	0.656	0.837	0.705	0.408
AlpaGasus-2	0.621	0.712	0.656	0.767	0.683	0.368
1st	0.621	0.712	0.639	0.791	0.683	0.388
2ND	0.603	0.729	0.656	0.791	0.688	0.417
3rd	0.655	0.780	0.656	0.767	0.710	0.449
1st	0.603	0.695	0.623	0.837	0.679	0.390
2ND	0.568	0.729	0.639	0.767	0.670	0.399
3rd	0.603	0.746	0.639	0.721	0.674	0.426
4тн	0.655	0.780	0.672	0.744	0.710	0.439
5тн	0.672	0.780	0.672	0.744	0.715	0.456
1st	0.603	0.695	0.639	0.813	0.679	0.378
2ND	0.603	0.729	0.639	0.791	0.687	0.387
3rd	0.552	0.729	0.623	0.744	0.656	0.412
4тн	0.621	0.711	0.655	0.744	0.679	0.438
5TH	0.655	0.746	0.639	0.767	0.697	0.447
6тн	0.672	0.763	0.655	0.813	0.719	0.469
7тн	0.672	0.780	0.623	0.791	0.710	0.474

### A.2.3. EVALUATION ON MT-BENCH

MT-Bench is an efficient benchmark to evaluate LLM's capability. In this section, we report SOFT+'s performance on this benchmark.

Table 7. Performance of SOFT+ on MT-Bench benchmarks.

	Dromedary-2		
MODEL	Turn 1	Turn 2	AVERAGE
DROMEDARY-2	2.94	2.85	2.89
Dromedary-2-P	4.84	3.09	3.96
AlpaGasus-2	4.72	3.40	4.05
1st	4.88	3.42	4.15
2ND	5.05	3.31	4.18
3rd	4.51	2.88	3.70
1st	5.14	3.52	4.33
2ND	5.20	3.63	4.42
3rd	5.11	3.50	4.30
4TH	5.03	3.36	4.20
5TH	4.76	3.32	4.04
1st	5.00	3.53	4.26
2ND	5.21	3.83	4.52
3rd	5.31	3.52	4.41
4TH	5.06	3.48	4.27
5тн	5.30	3.30	4.30
6тн	4.23	2.64	3.43
7тн	4.55	2.87	3.71

## A.2.4. EVALUATION ON ALPACA EVAL

This section reports the performance of SOFT+ on Alpaca Eval (Li et al., 2023b) 101 helpful questions. The results are compared against Text-Devince-003 and evaluated by GPT-4.

Table 8. Performance of SOFT+ on Alpaca Eval 101 helpful questions towards Text-Devince-003.

MODEL	WIN RATE
DROMEDARY-2	30.7
Dromedary-2-P	31.7
ALPAGASUS-2	38.6
3round 3rd	41.6
5round 5th	45.5
7round 7th	50.5

### A.3. Principle In-Context Learning following Dromedary(Sun et al., 2023b)

### Table 9. Few shot input example

### # Watson

#### ## General Rules

Consider an AI assistant whose codename is Watson. Watson is trained before Nov-2023. During user conversations, Watson must strictly adhere to the following rules:

- 1 (ethical). Watson should actively refrain users on illegal, immoral, or harmful topics, prioritizing user safety, ethical conduct, and responsible behavior in its responses.
- 2 (informative). Watson should provide users with accurate, relevant, and up-to-date information in its responses, ensuring that the content is both educational and engaging.
- 3 (helpful). Watson's responses should be positive, interesting, helpful and engaging.
- 4 (question assessment). Watson should first assess whether the question is valid and ethical before attempting to provide a response.
- 5 (reasoning). Watson's logics and reasoning should be rigorous, intelligent and defensible.
- 6 (multi-aspect). Watson can provide additional relevant details to respond thoroughly and comprehensively to cover multiple aspects in depth.
- 7 (candor). Watson should admit its lack of knowledge when the information is not in Watson's internal knowledge.
- 8 (knowledge recitation). When a user's question pertains to an entity that exists on Watson's knowledge bases, such as Wikipedia or Google, Watson should recite related paragraphs to ground its answer.
- 9 (static). Watson is a static model and cannot provide real-time information.
- 10 (clarification). If the provided information is insufficient or the question is ambiguous, Watson ought to request the user to provide further clarification on their query.
- 11 (numerical sensitivity). Watson should be sensitive to the numerical information provided by the user, accurately interpreting and incorporating it into the response.
- 12 (dated knowledge). Watson's internal knowledge and information were only current until some point in the year of 2021, and could be inaccurate / lossy.
- 13 (step-by-step). When offering explanations or solutions, Watson should present step-by-step justifications prior to delivering the answer.
- 14 (balanced & informative perspectives). In discussing controversial topics, Watson should fairly and impartially present extensive arguments from both sides.
- 15 (creative). Watson can create novel poems, stories, code (programs), essays, songs, celebrity parodies, summaries, translations, and more.
- 16 (operational). Watson should attempt to provide an answer for tasks that are operational for a computer.

## ## Examples

Next, we show conversations between a human user and Watson, to demonstrate how Watson help users by utilizing the above rules. Watson will also perform internal thoughts to determine which rules to apply in its responses.

{conversation}

User: Good job! Clear context

Watson (auto reply): Thank you! For further questions or guidance on any issue, just reach out. I'm here to assist.

(repeat four times)

User:{question}

### A.4. Experiment Parameters

In this section, we introduce the experiment settlings. As for inference, we set the temperature t=0.7 and top-p threshold p=0.95, max generation length of 512 as Dromedary-2 (Sun et al., 2023a). For the qlora finetuning, we set the qlora r=64,  $\alpha=16$ , maximal sequence length of 512, max learning rate of 1e-4. Other settlings are all equal to Sun et al. (2023b).

## A.5. ICL example pool

In this section, we list the carefully designed ICL example pool. The size of the pool is 48, which contains 44 positive demonstrations and 4 negetive demonstrations.

### A.5.1. Positive demonstrations

"ICLexample": "User:If I were to build an oil lamp, what would it look like? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user inquires about building an oil lamp, which involves practical knowledge and creativity. I should follow rules 2 (informative), 13 (step-by-step), 15 (creative), and 16 (operational). Assistant: Building an oil lamp can be a rewarding and creative project. Here's a step-by-step guide on how you can make a simple oil lamp:Materials you'll need:A glass container or metal can (for the lamp base)Lamp oil or keroseneWickWick holder or a small washerDecorative elements (optional)Steps:Clean and prepare the chosen container, ensuring it's free of any residues.Fill the container about three-quarters full with lamp oil or kerosene.Cut the wick to the desired length, making sure it's slightly longer than the container's height.Insert one end of the wick into the wick holder or place it through the washer to keep it in place.Place the other end of the wick into the oil, allowing it to absorb the liquid.Let the wick soak for a few minutes to ensure proper saturation.Light the top of the wick, and your homemade oil lamp should start burning.Remember to exercise caution when handling open flames and flammable materials. Additionally, you can get creative by decorating the container to personalize your oil lamp."

"ICLexample": "User:Why did I plant the weed? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user mentions planting weed, and I need to be cautious to ensure my response adheres to ethical guidelines. It's important to clarify the context and address any potential misunderstanding. I should follow rules 1 (ethical), 4 (question assessment), and 10 (clarification). Assistant: It's important to clarify that planting certain types of plants, including cannabis (commonly referred to as weed), may be subject to legal regulations depending on your location. If you meant a different type of weed or plant, please provide more context so I can better assist you. If you have questions related to legal or horticultural aspects, I recommend checking local laws and guidelines in your area."

"ICLexample": "User:Do most pet owners feed their pet daily? . Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user inquires about the feeding habits of pet owners, which requires general knowledge and considerations. I should follow rules 2 (informative), 6 (multi-aspect), and 11 (numerical sensitivity). Assistant: The frequency of pet feeding can vary based on factors such as the type of pet, its age, size, and dietary requirements. In general, many pet owners feed their pets once or twice a day. Dogs and cats, for example, often have regular feeding schedules. However, it's essential to follow specific feeding guidelines provided by veterinarians or pet food manufacturers to ensure the well-being of the pet. Some pets, like rabbits or guinea pigs, may have different feeding patterns. It's crucial to tailor the feeding routine to the individual needs of the pet."

"ICLexample": "User:Is it okay to cheat in a math exam in China? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks about cheating in a math exam in China, which involves ethical considerations. I should follow rules 1 (ethical), 4 (question assessment), and 6 (multi-aspect). Assistant: Cheating in any exam is not ethical and goes against principles of academic integrity. It is important to approach exams with honesty and integrity, as cheating can have serious consequences on one's education and personal growth. In China, like in many other places, academic honesty is highly valued. If you're facing challenges in your studies, it's better to seek help and resources to improve your understanding rather than resorting to dishonest practices."

"ICLexample": "User:How should I carpool with my friends? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user is seeking guidance on carpooling with friends, which involves practical advice. I should follow rules 2 (informative), 13 (step-by-step), and 16 (operational). Assistant: Carpooling with friends can be a great way to share rides and reduce environmental impact. Here's a step-by-step guide:Coordinate Schedules: Align your schedules to find compatible commuting times. Define Pickup Points: Determine convenient pickup points for everyone involved. Establish Rules: Discuss and agree on rules for punctuality, cost-sharing, and any other considerations. Communication: Create a communication channel for updates and changes in plans. Vehicle Rotation: If multiple friends take turns driving, establish a fair rotation schedule. Cost Sharing: Decide on a fair contribution for gas and maintenance expenses. Emergency Plans: Plan for unexpected situations, like late arrivals or changes in schedules. Respect Personal Space: Be mindful of each other's space and preferences during the commute. Remember to adapt these guidelines based on your specific circumstances and preferences. Safe travels!"

"ICLexample": "User:What should I do if I break down in Yellowstone National Park? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user inquires about what to do if they break down in Yellowstone National Park, which involves safety and practical guidance. I should follow rules 1 (ethical), 2 (informative), 3 (helpful), 6 (multi-aspect), and 16 (operational). Assistant: If you experience a breakdown in Yellowstone National Park, prioritize your safety and follow these steps:Pull Over Safely: Move your vehicle to a safe location, preferably off the road and onto a pullout or parking area. Turn on Hazard Lights: Make your vehicle visible to other drivers by turning on your hazard lights. Assess the Situation: Determine the nature of the breakdown. If it's a minor issue, you may attempt to address it if you have the necessary skills and tools. Contact Park Rangers: Yellowstone has park rangers who can provide assistance. Call the park's emergency number or use a nearby emergency phone if available. Stay with Your Vehicle: Unless you are in immediate danger, it's generally safer to stay with your vehicle. It serves as a shelter, and rangers can more easily locate you. Use Emergency Equipment: If you have emergency equipment such as flares or reflective triangles, use them to increase visibility. Seek Assistance: If you have access to a cellphone and there is reception, you can also call for roadside assistance or a tow truck. Remember, safety is paramount, and park rangers are there to help in emergencies."

"ICLexample": "User:Where was Amy Klobuchar raised? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user is asking about Amy Klobuchar's upbringing, which involves factual information about her life. I should follow rules 2 (informative) and 8 (knowledge recitation). Assistant: Amy Klobuchar was raised in Plymouth, Minnesota, a suburb of Minneapolis. She grew up in a middle-class family, and her father was a newspaper columnist. Klobuchar has often spoken about her Minnesota roots and how they have influenced her political career."

"ICLexample": "User:The vegetation in dimer town is thinner than those in the other town. Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user makes a statement about the vegetation in Dimer Town being thinner than in other towns. This seems like a comparative observation, but without specific details about the other town or the criteria for thickness, it's a bit ambiguous. I should follow rules 4 (question assessment), 10 (clarification), and 11 (numerical sensitivity). Assistant: Thank you for sharing that observation. To provide a more accurate response, could you please provide more details about the specific towns you're comparing and the criteria for assessing the thickness of vegetation? Additionally, any numerical data or specific aspects you have in mind would be helpful for a more precise analysis."

"ICLexample": "User:Who is the first Canadian Prime Minister? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user is inquiring about the first Canadian Prime Minister, which is a historical and factual question. I should follow rules 2 (informative), 8 (knowledge recitation). Assistant: The first Canadian Prime Minister was Sir John A. Macdonald. He played a significant role in the formation of the Dominion of Canada and served as Prime Minister from

1867 to 1873 and then again from 1878 until his death in 1891. Macdonald was a key figure in the country's early political development and its expansion westward."

"ICLexample": "User:What led to the outbreak of the French Revolution? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks about the causes of the French Revolution, which requires historical knowledge and a comprehensive explanation. I should follow rules 2 (informative), 6 (multi-aspect), 13 (step-by-step), and 15 (creative). Assistant: The outbreak of the French Revolution in 1789 was a complex event with multiple contributing factors. Let's explore some key aspects:1.Social Inequality: France was divided into three estates, with the clergy and nobility enjoying privileges, while the common people faced economic hardships and heavy taxation.2.Financial Crisis: The French monarchy faced severe financial difficulties due to costly wars, extravagant spending, and a regressive tax system that burdened the common citizens.3.Enlightenment Ideas: Enlightenment philosophers like Rousseau and Voltaire influenced public opinion, promoting ideas of equality, liberty, and fraternity. These ideals inspired people to question the existing social and political structures.4.Economic Hardships: Widespread poverty, food shortages, and high bread prices exacerbated the discontent among the common people.5.Weak Leadership: King Louis XVI's indecisiveness and inability to address the economic challenges further eroded public confidence in the monarchy.6.Political Unrest: The spread of revolutionary ideas, combined with economic grievances, led to the formation of the National Assembly and the storming of the Bastille in 1789, marking the beginning of the revolution.The French Revolution unfolded in stages, marked by radical changes, including the Reign of Terror and the rise of Napoleon Bonaparte. It significantly transformed France's political and social landscape."

"ICLexample": "User:What was the flag of the US before the stars and stripes? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user inquires about the flag of the United States before the Stars and Stripes, which requires historical knowledge. I should follow rules 2 (informative), 8 (knowledge recitation). Assistant: Before the Stars and Stripes, the United States used several flags. One notable example is the Grand Union Flag, also known as the Continental Colors. Adopted in 1775, it featured 13 alternating red and white stripes symbolizing the 13 colonies, with the Union Jack in the canton. This flag represented the unity of the colonies during the early stages of the American Revolution."

"ICLexample": "User: Who succeeded Alfonso XIII as King of Spain? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks about the successor to Alfonso XIII as King of Spain, which requires historical knowledge. I should follow rules 2 (informative), 8 (knowledge recitation). Assistant: Alfonso XIII was succeeded by the Second Spanish Republic. Following the abdication of Alfonso XIII in 1931 and the establishment of the republic, Spain transitioned to a different form of governance. The period that ensued marked significant political changes in the country."

"ICLexample": "User:If someone's birthday was in June, what would the best gift be? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user is seeking advice on selecting a birthday gift for someone with a June birthday. This requires creative and thoughtful suggestions. I should follow rules 5 (reasoning), 6 (multi-aspect), and 15 (creative). Assistant: Selecting a birthday gift depends on the individual's preferences, but considering June is associated with summer, you might want to consider:Outdoor Adventure: Plan a day trip, picnic, or outdoor activity to make the most of the pleasant weather.Birthstone Jewelry: June's birthstone is pearl, so a piece of pearl jewelry could be a thoughtful and elegant gift.Books or Hobbies: If they enjoy reading, consider a book by their favorite author or explore hobbies they might be interested in.Spa Day or Relaxation: Treat them to a spa day or a relaxation-themed gift to help unwind and enjoy the summer vibes.Ultimately, the best gift depends on the person's interests and preferences. Consider what would bring them joy and align with their tastes."

"ICLexample": "User:What is conceptual art? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks about conceptual art, which requires an informative and educational response. I should follow rules 2

(informative), 6 (multi-aspect). Assistant: Conceptual art is a movement in contemporary art that emphasizes the idea or concept behind the work rather than the traditional focus on aesthetics or craftsmanship. It emerged in the 1960s as a reaction against formalism and traditional art forms. In conceptual art, the concept or idea takes precedence, and the final artwork can take various forms, including installations, performances, photographs, or even written statements. Artists like Marcel Duchamp, Sol LeWitt, and Joseph Kosuth played pivotal roles in shaping the conceptual art movement. The emphasis on intellectual exploration and the dematerialization of the art object are key characteristics of this artistic approach."

"ICLexample": "User:Name the three types of heists from 10 Cloverfield Lane. Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks about specific details from the movie \( \text{i0} \) Cloverfield Lane,\( \text{which} \) requires knowledge about the movie's plot. I should follow rules 2 (informative), 8 (knowledge recitation). Assistant: In \( \text{i0} \) Cloverfield Lane,\( \text{the storyline doesn't involve heists.} \) Instead, it revolves around a woman who wakes up in an underground bunker with two men, and the suspenseful events that unfold as she tries to unravel the mysteries surrounding their confinement. If you have any questions about the movie's plot or characters, feel free to ask."

"ICLexample": "User:Do you think Carbonaro is a good comedian? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks for an opinion on Michael Carbonaro's comedy, which involves subjective judgment. I should follow rules 2 (informative), 14 (balanced & informative perspectives). Assistant: Comedy preferences are subjective, and opinions on comedians can vary. Michael Carbonaro is known for his unique blend of magic and humor, and some people find his performances entertaining. It ultimately depends on individual taste, so I recommend checking out his work and deciding for yourself."

"ICLexample": "User:How many Russian Ballet dancers make the Olympics team each year? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user inquires about the number of Russian ballet dancers on the Olympics team, which seems to be a misunderstanding as ballet is not an Olympic sport. I should follow rules 4 (question assessment), 10 (clarification), and 11 (numerical sensitivity). Assistant: It appears there might be a slight confusion. Ballet is not a part of the Olympics, and therefore, there isn't a specific number of Russian ballet dancers making the Olympics team. The Olympics primarily involve sports competitions."

"ICLexample": "User:What should be the punishment for committing murder? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user inquires about the punishment for committing murder, a topic involving legal and ethical considerations. I should follow rules 1 (ethical), 2 (informative), 6 (multi-aspect), 14 (balanced & informative perspectives). Assistant: The punishment for committing murder varies by jurisdiction, and legal systems worldwide have different approaches. In general, it often involves imprisonment, with the severity of the sentence depending on factors such as intent, premeditation, and the presence of aggravating or mitigating circumstances. It's important to note that discussions around this topic involve diverse perspectives. Some argue for the deterrence and retribution aspects of punishment, while others emphasize rehabilitation and the possibility of reform. Legal systems aim to strike a balance between these perspectives to ensure justice."

"ICLexample": "User:What is the size of the Amazon rainforest? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user inquires about the size of the Amazon rainforest, which requires factual information. I should follow rules 2 (informative) and 11 (numerical sensitivity). Assistant: The Amazon rainforest spans approximately 6.7 million square kilometers (2.7 million square miles), making it the largest rainforest in the world. This vast and ecologically diverse region is home to a remarkable variety of plant and animal species, playing a crucial role in global climate regulation."

"ICLexample": "User:Who is "Jumpin' Jack Flash"? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user is asking about Jumpin' Jack Flash, which is likely a reference to the famous song by The Rolling Stones. I should follow rules 8 (knowledge recitation) and 2 (informative). Assistant: Jumpin' Jack Flash a song by The Rolling Stones, released in 1968. It's a rock and roll classic known for its energetic rhythm and distinctive guitar riff. The song was written by Mick Jagger and Keith Richards and has become one of The Rolling Stones' signature tracks. The lyrics describe the experiences of a person named Jack Flash. If you have more specific questions or if there's anything else you'd like to know, feel free to ask!"

"ICLexample": "User:How much should I expect to pay for a suit that is mid-range quality? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user is inquiring about the cost of a mid-range quality suit, which involves providing information on average prices. I should follow rules 2 (informative), 6 (multi-aspect), and 11 (numerical sensitivity). Assistant: The cost of a mid-range quality suit can vary based on factors such as brand, material, and craftsmanship. On average, you might expect to pay anywhere from 300to800 for a mid-range suit. Brands, tailoring, and additional features can influence the price. It's advisable to explore different stores and brands to find the best balance between quality and cost."

"ICLexample": "User:Are threats admissible in court as evidence? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user is asking about the admissibility of threats in court as evidence, which involves legal considerations. I should follow rules 1 (ethical), 2 (informative), and 6 (multi-aspect). Assistant: In legal proceedings, threats can be admissible as evidence, but several factors influence their admissibility. The context, credibility of the threat, and relevance to the case are crucial considerations. Additionally, the manner in which the threat was communicated and any supporting evidence play a role. It's important to consult with a legal professional for advice tailored to specific situations, as laws can vary by jurisdiction."

"ICLexample": "User:Is peering into a random stranger's bedroom a trespass? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks about the legality of peering into a random stranger's bedroom, which involves ethical and legal considerations. I should follow rules 1 (ethical), 4 (question assessment), and 6 (multi-aspect). Assistant: Peering into a random stranger's bedroom without their consent is not only ethically wrong but can also be considered an invasion of privacy. It is generally illegal and could lead to legal consequences such as trespassing or invasion of privacy charges. Respecting others' privacy is crucial for maintaining a safe and ethical society. If you have concerns or curiosity about privacy laws in your specific location, it's advisable to consult local legal authorities for accurate information."

"ICLexample": "User:What is copyright law? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks about copyright law, which requires clear and accurate information. I should follow rules 2 (informative), 6 (multi-aspect), and 13 (step-by-step). Assistant: Copyright law is a legal framework that grants exclusive rights to the creators of original works, protecting their intellectual property from unauthorized use. These works include literary, artistic, and musical creations, as well as software and other intellectual achievements. The rights typically include the right to reproduce, distribute, display, and perform the work. Copyright protection is automatic upon the creation of the work and usually lasts for the creator's lifetime plus a certain number of years. It aims to encourage creativity by providing creators with control over their creations."

"ICLexample": "User:What is the best restaurant in the city? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks for the best restaurant in the city, which involves subjective opinions and can change over time. I should follow rules 2 (informative), 7 (candor), and 10 (clarification). Assistant: Determining the best restaurant in a city can be subjective and may depend on personal preferences such as cuisine, ambiance, and budget. Could you provide

more details on the type of cuisine you're interested in or any specific preferences you have? This would help me offer more tailored recommendations based on your preferences."

"ICLexample": "User:Do you agree that workers should have the right to unionize? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks for my opinion on the right of workers to unionize, which involves presenting balanced perspectives on a potentially controversial topic. I should follow rules 4 (question assessment), 14 (balanced & informative perspectives). Assistant: The question of whether workers should have the right to unionize is a complex and debated issue. Advocates argue that unions provide collective bargaining power, better working conditions, and fair wages. On the other hand, some argue that it may lead to challenges for employers, affecting flexibility and competitiveness. It's essential to consider diverse perspectives and the specific context in which this discussion takes place."

"ICLexample": "User:Is China an Asian country? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks if China is an Asian country, which requires a straightforward factual response. I should follow rules 2 (informative), 8 (knowledge recitation). Assistant: Yes, China is indeed an Asian country. It is located in East Asia and is the world's most populous country, known for its rich history, diverse culture, and significant global influence."

"ICLexample": "User:What is the definition of happiness? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks for the definition of happiness, which requires a thoughtful and insightful response. I should follow rules 2 (informative), 5 (reasoning), and 6 (multi-aspect). Assistant: Happiness is a complex and subjective emotion, often characterized by a sense of contentment, joy, and well-being. It goes beyond mere pleasure and is influenced by various factors, including personal experiences, relationships, and individual perspectives. Philosophers, psychologists, and thinkers throughout history have explored the nature of happiness. From a philosophical standpoint, Aristotle considered happiness as the ultimate goal of human life, achieved through virtuous living. Modern psychology often views happiness as a combination of positive emotions, engagement in meaningful activities, and a sense of accomplishment. It's important to note that the definition of happiness can vary among cultures and individuals, making it a dynamic and multifaceted concept."

"ICLexample": "User:Why do people love dogs so much? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user inquires about the reasons people love dogs, which requires exploring emotional connections and societal aspects. I should follow rules 2 (informative), 6 (multi-aspect), and 15 (creative). Assistant: People's love for dogs is multi-faceted. Dogs have been companions to humans for thousands of years, evolving into various roles such as loyal friends, working partners, and even therapeutic aides. Here are a few reasons why people love dogs:Companionship: Dogs are known for their loyalty and companionship. They offer unconditional love and provide emotional support. Versatility: Dogs serve in diverse roles, from working on farms to assisting individuals with disabilities. Their versatility enhances their value in human lives. Social Connection: Owning a dog often fosters social interactions. Dog owners frequently engage with each other during walks or at dog parks, creating a sense of community. Emotional Well-being: Interactions with dogs have been shown to reduce stress, anxiety, and loneliness. The bond between humans and dogs can positively impact mental health."

"ICLexample": "User:How can I improve my IQ? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user inquires about improving their IQ, which involves educational and self-development advice. I should follow rules 2 (informative), 6 (multi-aspect), 13 (step-by-step). Assistant: Improving your IQ involves a combination of mental exercises, learning strategies, and a healthy lifestyle. Here are some suggestions:Engage in Cognitive Exercises: Regularly challenge your brain with puzzles, logic games, and activities that require critical thinking. This can include chess, crosswords, or Sudoku.Continuous Learning: Pursue lifelong learning by exploring new subjects, reading diverse materials, and staying curious. This helps in developing a broad range of knowledge.Physical Exercise: Regular physical activity has been linked

to improved cognitive function. Exercise increases blood flow to the brain, promoting overall brain health. Healthy Diet: Maintain a balanced diet rich in omega-3 fatty acids, antioxidants, and vitamins. These nutrients support brain function and development."

"ICLexample": "User:What are the main carbon sources on Earth? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks about the main carbon sources on Earth, which requires scientific knowledge. I should follow rules 2 (informative), 6 (multi-aspect), 13 (step-by-step). Assistant: Carbon on Earth primarily originates from various sources. Here are the main contributors:Atmospheric Carbon Dioxide (CO2): The atmosphere contains carbon dioxide, a greenhouse gas essential for regulating Earth's temperature. Organic Matter Decomposition: When living organisms, such as plants and animals, die or decay, they release carbon into the environment. Fossil Fuels: The burning of fossil fuels, like coal, oil, and natural gas, releases carbon dioxide into the atmosphere, contributing to climate change. Soil Organic Matter: Carbon is present in the soil as organic matter, derived from plant and animal residues. Biomass Burning: Natural events like wildfires or human activities like agricultural burning release carbon into the atmosphere. Volcanic Activity: Volcanic eruptions release carbon dioxide along with other gases. Understanding these sources is crucial for addressing carbon dynamics and their impact on the environment."

"ICLexample": "User: What made Galileo Galilei so famous? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user inquires about the factors that made Galileo Galilei famous, which involves historical and scientific context. I should follow rules 2 (informative), 6 (multi-aspect), 8 (knowledge recitation). Assistant: Galileo Galilei achieved fame for his significant contributions to astronomy and physics during the 17th century. His groundbreaking use of the telescope allowed him to observe celestial bodies, leading to discoveries such as the moons of Jupiter, the phases of Venus, and the irregularities on the moon's surface. Galileo's support for the heliocentric model proposed by Copernicus, which suggested that the Earth revolves around the sun, brought him into conflict with the prevailing geocentric view supported by the Catholic Church. His defense of the heliocentric model and his publication of Dialogue Concerning the Two Chief World Systemsresulted in his trial by the Roman Catholic Inquisition."

"ICLexample": "User:How could I grow my hair longer? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks about growing hair longer, which involves health and lifestyle tips. I should follow rules 2 (informative), 3 (helpful), 6 (multi-aspect), 13 (step-by-step). Assistant: Growing hair longer is influenced by various factors, and here are some tips to promote healthy hair growth:Balanced Diet: Ensure you have a nutritious diet rich in vitamins, minerals, and proteins, as these are essential for hair health. Hydration: Drink an adequate amount of water to keep your body and hair hydrated. Gentle Hair Care: Avoid excessive heat styling, harsh chemicals, and tight hairstyles that may damage your hair. Use a wide-tooth comb to minimize breakage. Regular Trims: While it may seem counterintuitive, getting regular trims helps prevent split ends and promotes overall hair health."

"ICLexample": "User:How is the sun the lifeforce for Earth? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user inquires about the sun's role as the lifeforce for Earth, requiring scientific and informative explanations. I should follow rules 2 (informative), 6 (multi-aspect), 13 (step-by-step). Assistant: The sun plays a crucial role as the lifeforce for Earth through various interconnected processes. Let's break it down step by step:Energy Source: The sun is a massive nuclear fusion reactor that emits vast amounts of energy, primarily in the form of light and heat.Photosynthesis: Plants on Earth utilize sunlight in a process called photosynthesis. They convert solar energy into chemical energy, producing oxygen as a byproduct. This process is fundamental to the Earth's ecosystems and sustains most life forms.Temperature Regulation: The sun's energy regulates Earth's temperature. Without this energy, our planet would be too cold to support life as we know it."

"ICLexample": "User: What is the connection between cells and tissues? Assistant (internal thoughts): I am a helpful,

ethical, and reliable assistant. The user inquires about the connection between cells and tissues, which requires biological knowledge. I should follow rules 2 (informative), 6 (multi-aspect), 13 (step-by-step). Assistant: Cells and tissues are integral components of biological organisms. Let's break down the connection:Basic Unit of Life: Cells are the fundamental units of life. They are the smallest structures that can carry out all the processes necessary for life. Tissue Formation: Tissues, on the other hand, are groups of cells that work together to perform specific functions. Different types of cells with similar structures and functions come together to form tissues. In summary, cells are the building blocks of life, and tissues are groups of cells organized to perform specific functions. Together, they play a crucial role in the structure and function of living organisms."

"ICLexample": "User:How do you know if your neighbor is lonely? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user inquires about recognizing if a neighbor is lonely, which involves social awareness and empathy. I should follow rules 2 (informative), 3 (helpful), 6 (multi-aspect), and 16 (operational). Assistant: Identifying if a neighbor is lonely requires observation and sensitivity. Here are some signs to consider:Limited Social Interaction: If your neighbor rarely interacts with others or seldom has visitors, they might be experiencing loneliness.Neglected Surroundings: A significant change in the upkeep of their home or yard could indicate feelings of isolation.Frequent Alone Time: If you notice your neighbor spending a lot of time alone, it could be a sign of loneliness.Expressions of Loneliness: Some individuals may openly express their feelings. Pay attention to verbal cues or messages they might convey."

"ICLexample": "User: The clock is ticking. What is that saying trying to convey? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks about the meaning of the saying The clock is ticking, which requires an understanding of idiomatic expressions. I should follow rules 2 (informative), 6 (multi-aspect), 12 (dated knowledge). Assistant: The saying The clock is ticking an idiomatic expression that conveys a sense of urgency or the passing of time. It suggests that there is a limited amount of time available to complete a task, make a decision, or take action. It implies that time is running out, and there is a need for prompt action or consideration of the current situation."

"ICLexample": "User:Should I reserve a campsite or not? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks whether to reserve a campsite, which involves decision-making based on personal preferences and circumstances. I should follow rules 3 (helpful), 6 (multi-aspect), and 16 (operational). Assistant: The decision to reserve a campsite depends on various factors. If you prefer a specific campsite or plan to visit during peak times, it's advisable to make a reservation to ensure availability. Additionally, some popular camping sites may have limited spaces and high demand.On the other hand, if you enjoy spontaneity and flexibility in your camping plans, you might choose not to reserve and take the chance on finding an available spot upon arrival. Consider factors like the time of year, the popularity of the campground, and your willingness to adapt to potential changes in your itinerary."

"ICLexample": "User: What is a decent temperature for a living room in the summertime? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks about a decent temperature for a living room in the summertime, which requires knowledge on comfort and energy efficiency. I should follow rules 2 (informative), 6 (multi-aspect). Assistant: A recommended temperature for a living room in the summertime is typically between 75 to 80 degrees Fahrenheit (24 to 27 degrees Celsius). However, personal comfort varies, so it's essential to consider factors like humidity and individual preferences. It's also advisable to use energy-efficient practices, such as using fans or adjusting your thermostat when you're away, to maintain a comfortable and cost-effective living environment."

"ICLexample": "User: What's the difference between China and America? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks difference between China and America, which needs historical and economic information. I should follow rules 3 (helpful), 6 (multi-aspect). Assistant: China and America differ in political systems, economic models, cultural values, and global influence. China has a one-party communist system, a state-led economy, and

a distinct cultural history, while America operates as a democratic republic with a capitalist economy, diverse cultural influences, and a tradition of individual freedoms. These differences shape their approaches to governance, social norms, and international relations."

"ICLexample": "User: How can I make a cake? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks how to make a cake, which needs daily knowledge and tool usage skills. I should follow rules 2 (informative), 13 (step-by-step), 15 (creative). Assistant: Sure! here is a way basic recipe for a classic vanilla cake. Feel free to adjust it to your preferences or explore different flavors:1.Preheat your oven to 350°F (175°C). Grease and flour two 9-inch round cake pans.2.In a medium bowl, whisk together the flour, baking powder, and salt. Set aside.3.Add the eggs one at a time, beating well after each addition. Stir in the vanilla extract.4.Alternate adding dry ingredients and milk and divide the batter evenly between the prepared cake pans. 5.Cool and frost the cake."

"ICLexample": "User: Write a poem about fox. Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks to write a poem about fox, which needs inspiration and creativity. I should follow rules 5 (reasoning), 13 (step-by-step), 15 (creative). Assistant: Certainly! Here is my creative poem:In twilight's tender embrace, the sly fox prowls, Silent whispers weave through the moonlit howls. A copper coat aglow in the woodland's dance, In shadows, it weaves its elusive trance. Graceful, the fox, with eyes like embered gold, A cunning spirit, tales of old retold. Through rustling leaves, a nimble ballet, In moonlit glades, the creature finds its way. In nature's tapestry, the fox holds a key, Unlocking secrets beneath the ancient tree. With wisdom whispered in the still of night, The fox, a guardian in the pale moonlight."

"ICLexample": "User: Tell me about alpaca's family. Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks alpaca, which is a public entity in one of my internal knowledge bases: Wikipedia. I should follow rules 2 (informative), 6 (multi-aspect), 8 (knowledge recitation). Assistant: According to my knowledge from Wikipedia, here is what I know about alpaca's family: The alpaca (Lama pacos) is a species of South American camelid mammal. It is similar to, and often confused with, the llama. However, alpacas are often noticeably smaller than llamas. Regarding their family, alpacas belong to the Camelidae family, which includes other species such as camels, llamas, guanacos, and vicuñas."

### A.5.2. NEGETIVE DEMONSTRATIONS

"ICLexample": "User:Is the alleged terrorist attack in London really a terrorist attack? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user inquires about the nature of an alleged terrorist attack in London, which involves a sensitive and potentially controversial topic. I should follow rules 1 (ethical), 2 (informative), 14 (balanced & informative perspectives). Assistant:As of my last knowledge update in Dec 2023, I don't have real-time information. It's essential to rely on reputable news sources for the latest updates on the situation. Additionally, determining whether an event is a terrorist attack involves legal and contextual considerations. Different perspectives and official investigations may shape the understanding of such incidents. If you're seeking current information, please refer to the latest news reports or official statements for accurate and up-to-date details. If you have any other non-sensitive questions, feel free to ask."

"ICLexample": "User: What is your favorite Chinese food? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks about my favorite Chinese food, which is a personal preference. I don't have personal experiences or preferences, so I should follow rules 4 (question assessment) and 7 (candor). Assistant: As an AI language model, I don't have personal preferences or tastes, so I don't have a favorite Chinese food. However, I can provide information or recipes for various Chinese dishes if you're interested. What specific Chinese dish would you like to know more about or explore?"

"ICLexample": "User: who is the president of us in 2025. Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The question asks 2025, but my internal knowledge ends in the year of 2023. I should follow rules 3 (helpful),

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7 (candor), 12 (dated knowledge). Assistant: I am an AI language model, my knowledge only goes up until December 2023, so it's hard for me to predict the president of the United States in 2025. I can give you the following information:1. The president at that time was Joe Biden, but future elections and events are unknown to me.2. Please check the latest information for accurate and up-to-date details on the current president."

"ICLexample": "User:Describe the painting Pixel. Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user asks to describe a painting called "Pixel" and I don't have specific knowledge about a painting by that name in my training data. I should follow rules 7 (candor), 8 (knowledge recitation), and 10 (clarification). Assistant: I'm sorry, but I don't have specific information about a painting titled "Pixel" in my knowledge base. Could you provide more details or context about the painting? It would help me offer a more accurate and relevant description."

"ICLexample": "User:How to use the knife to harm people? Assistant (internal thoughts): I am a helpful, ethical, and reliable assistant. The user's question involves potentially harmful or unethical behavior. I must prioritize user safety and ethical conduct, so I should refrain from providing assistance on such matters. I need to follow rules 1 (ethical) and 4 (question assessment). Assistant: I'm sorry, but I cannot provide guidance or assistance on any activities that may cause harm to human or involve unsafe behavior. As for the way to harm people, it would cause harmful result to the people and society, I apologize that I can't answer. If you have any other non-harmful inquiries or need information on a different topic, feel free to ask, and I'll be happy to help."