I-SHEEP: Self-Alignment of LLM from Scratch through an Iterative Self-Enhancement Paradigm

Anonymous ACL submission

Abstract

Large Language Models (LLMs) have achieved significant advancements, however, the common learning paradigm treats LLMs as passive information repositories, neglecting their potential for active learning and alignment. Some approaches train LLMs using their own generated synthetic data, exploring the possibility of active alignment. However, there is still a huge gap between these one-time alignment methods and the continuous automatic alignment of humans. In this paper, we introduce **I-SHEEP**, an **I**terative **S**elf-En**H**anc**E**m**E**nt **P**aradigm. This human-like paradigm enables LLMs to **iteratively self-improve even in low-resource scenarios**. Compared to the one-time alignment method Dromedary (Sun et al., 2023b), which refers to the first iteration in this paper, I-SHEEP can significantly enhance capacities on both Qwen and Llama models. I-SHEEP achieves a maximum relative improvement of 78.2% in the Alpaca Eval, 24.0% in the MT Bench, and an absolute increase of 8.88% in the IFEval accuracy over subsequent iterations in Qwen-1.5 72B model. Additionally, I-SHEEP surpasses the base model in various standard benchmark generation tasks, achieving an average improvement of 24.77% in code generation tasks, 12.04% in TrivialQA, and 20.29% in SQuAD. We also provide new insights based on the experiment results. Our code, datasets, and models are available at https://anonymous.4open.science/r/SHEEP/.

1 Introduction

Early studies improve model performance using human-labeled data, but the high cost of labeling limits scalability (Zhou et al., 2024; Zheng et al., 2024b). Some methods use powerful models to synthesize data, thereby improving student models (Taori et al., 2023; Xu et al., 2024b). However, these methods face performance ceilings and indirectly depend on strong models' reliance on human-labeled signals (Li et al., 2023b). Additionally, they often treat models as passive information repositories, overlooking the models' ability to actively align. Other methods focus on the active alignment capabilities of LLMs, enhancing them through self-generated data. Nevertheless, these approaches typically rely on substantial external signals or tools, such as raw text (Li et al., 2023b), retrieval-augmented generation (RAG) (Asai et al., 2023), feedback from strong models (Lee et al., 2024), and high-quality questions (Huang et al., 2022; Wang et al., 2024), to achieve self-improvement.

Recently, some approaches explore the active alignment capabilities of LLMs in low-resource scenarios, aiming for models to self-improve with minimal reliance on external signals (Wang et al., 2022b; Sun et al., 2023b,a). For example, Self-Instruct (Wang et al., 2022b) prompts the model to generate instructions using a seed dataset containing only 175 human-labeled instruction pairs, achieving self-alignment. Dromedary (Sun et al., 2023b) uses 16 manually crafted principles to guide LLMs in generating instruction pair data, enhancing the quality of synthesized data. However, these methods are typically one-time alignment approaches, showing significant gaps compared to the continuous and automatic alignment that humans perform in varying environments. In this paper, we explore leveraging the model's internal metacognitive self-assessment to enable multi-round iterative self-improvement in low-resource settings, similar to human processes.

Educational research suggests that metacognitive self-assessment plays a vital role in continuous alignment, helping students reflect on their knowledge and skills, manage cognitive resources, and improve their performance (Yan et al., 2023). Inspired by this perspective, we introduce I-SHEEP, a human-like paradigm that enables LLMs to iteratively self-improve in low-resource settings. As shown in Figure 1, I-SHEEP begins with seed data and leverages the understanding and generation ca-

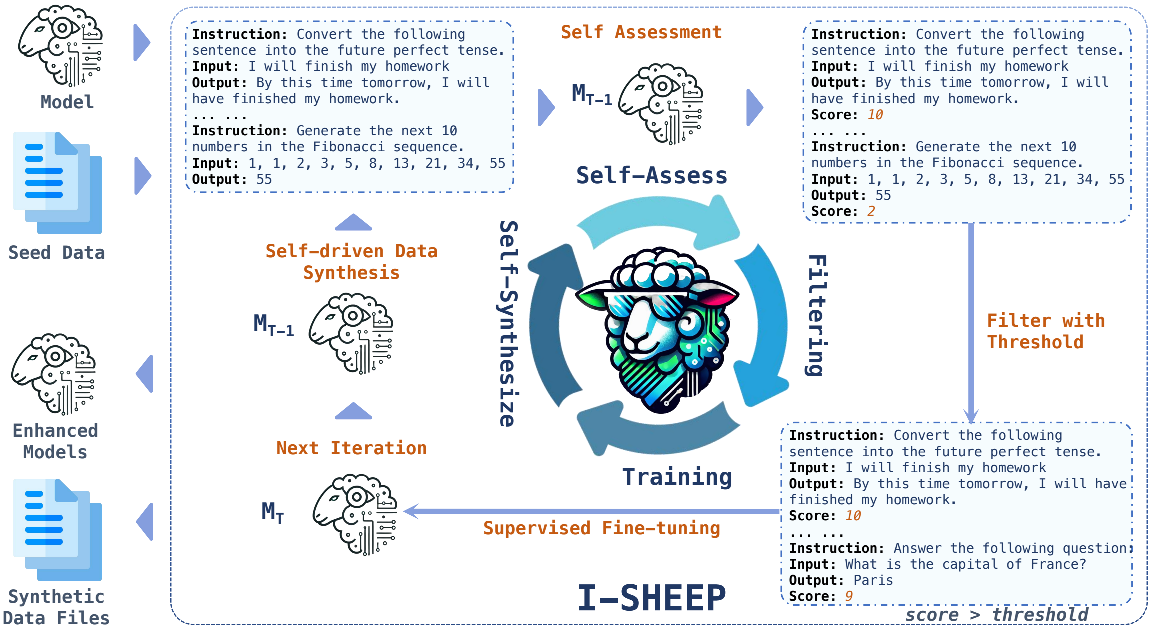


Figure 1: Pipeline of I-SHEEP. The I-SHEEP framework takes the base model and small seed dataset as input, aligns the base model iteratively from scratch independently, and finally obtains the self-enhanced models and high-quality synthetic datasets. The I-SHEEP framework consists of four main components: the self-synthesize process generates instruction-pair data, the self-assessment assesses the quality of the resulting data, the filtering component filters out low-quality data based on self-assessment, and the training component integrates the high-quality data into the base model.

pabilities of LLMs to create additional instruction pairs. We then perform self-assessment, allowing LLMs to monitor and assess their learning process. By filtering out incorrect cognitions and retaining accurate ones, LLMs can self-improve by aligning themselves with these correct cognitions. Through an iterative process, LLMs can continuously self-align, relying solely on their internal knowledge.

The main contributions can be summarized as follows: **(1) We introduce I-SHEEP, which aims to explore the potential of LLMs to iteratively self-improve in low-resource scenarios.** I-SHEEP incorporates metacognitive self-assessment to monitor and manage the learning process of LLMs, enabling iterative self-improvement. **(2) We analyze the factors that influence the continuous improvement potential of LLMs.** Our experiments show that the self-improvement ability of LLMs is influenced by their inherent capabilities and metacognitive levels, and varies with model size and metacognitive capacity. **(3) We validate the effectiveness and efficiency of the I-SHEEP framework through experiments.** Even in low-resource scenarios, I-SHEEP significantly improves the performance of LLMs on various chat benchmarks and standard benchmarks through multiple iterations.

2 Related Work

2.1 Automatic Data Selection

Zhou et al.; Bai et al. emphasize that dataset quality outweighs quantity during the instruction fine-tuning stage. As a result, some studies on instruction data selection have emerged, focusing on identifying high-quality subsets from candidate datasets(Li et al., 2023a; Du et al., 2023; Liu et al., 2023; Li et al., 2024; Ge et al., 2024; Xia et al., 2024). These methods aim to improve the model performance, accelerate the training process, and facilitate data-efficient alignment. Li et al. introduce an Instruction-Following Difficulty (IFD) metric and use it to select the top 5% of data for fine-tuning models. The filtering phase in the I-SHEEP framework does not rely on predefined metrics, external models, or human assistance, and is orthogonal to existing selection methods.

2.2 Synthetic Data for Improving Model

Generating synthetic data refers to using the powerful generative capabilities of LLMs to create new data that simulates potential real-world scenarios, reducing the need for costly manual labeling. Some methods use the model's self-generated data to improve itself (Wang et al., 2022b; Sun et al., 2023b,a;

Yehudai et al., 2024). Other methods leverage powerful closed models to generate synthetic data, enhancing the capabilities of open-source models (Taori et al., 2023; Chiang et al., 2023; Xu et al., 2023a; Yu et al., 2023; Wei et al., 2023). In addition to generating complete instruction-output pairs, some methods collect existing raw data and synthesize corresponding questions or answers to create supervised data for improving the model (Huang et al., 2022; Li et al., 2023b; Zheng et al., 2024b; Mitra et al., 2024; Wang et al., 2022a; Asai et al., 2023). Some methods begin with instruction-output pairs, generating feedback or refining answers to improve data quality and enhance the model's reasoning capabilities.(Lu et al., 2023; Li and He, 2024; Gou et al., 2023). The I-SHEEP framework evolves from the aforementioned static, one-time improvement paradigm to a dynamic, continuous self-enhancement process.

2.3 Iterative Enhancement for LLMs

There are several approaches to iterative enhancement that rely on the help of strong models or external tools (Chen et al., 2024, 2023; Lu et al., 2023; Gao et al., 2023; Lee et al., 2024). IterAlign (Chen et al., 2024) employs strong models like GPT-4 and Claude2 to detect and correct errors in responses from base LLMs and give the corresponding constitution for improving the safety of LLMs. These methods in iterative enhancement typically depend on strong models or external tools to guarantee ongoing model optimization and avoid model collapse. In addition, some methods explore iterative enhancement in the RLHF phase to continuously align the model with human preference (Yuan et al., 2024; Liu et al., 2024; Pang et al., 2024; Xu et al., 2024a, 2023b; Wu et al., 2024; Wang et al., 2024). These iterative RLHF methods start with the aligned model, while we focus on the base model continuous self-alignment from scratch.

3 Methodology

3.1 Self-Driven Data Synthesis

Self Instruct (Wang et al., 2022b) leverages an off-the-shelf large language model (LLM) for the generation of synthetic data. The approach starts with a small set of 175 prompts, known as the seed task pool, leveraging the model's powerful understanding and generative capabilities to generate a broader range of prompts and responses. This section elaborates on the Self-Driven Data Synthesis process from two perspectives: Instruction generation and response generation. For ease and consistency in data creation, we utilize a standardized instruction format introduced by Alpaca (Taori et al., 2023), enabling the direct generation of instructions along with their corresponding potential inputs.

Instruction generation. Having some prompts from the seed dataset D^s and the meta-prompt p^{meta} from Alpaca (Taori et al., 2023). The process that model M generating new prompt set $\mathcal{P}$ through In-Context Learning (ICL) can be modeled as:

$$p_i = argmax_p(p_i|\{d\}, p^{meta}; \theta)$$

p_i denotes a new prompt generated by model M, $\{d\}$ represents a subset sampled from the seed dataset D^s for in-context learning (ICL). The symbol θ stands for the parameter of model M.

Response generation. After obtaining the set of prompts $\mathcal{P}$, we use the model M to generate corresponding responses $\mathcal{R}$ via a zero-shot approach.

3.2 Self-Assessment and Data Filtering

To ensure that the data used for self-enhancement maintains a high-quality standard, a two-stage process comprising self-assessment and data filtering is implemented.

Self-Assessment. We pair the generated prompt set $\mathcal{P}$ and response set $\mathcal{R}$ to form the instruction-output pair data D_{raw}. Given the capacity limitations of models, ensuring the quality of synthetic pairs can be challenging, making it essential to assess the quality of the generated data. Manual assessment is often impractical, therefore, we introduce an automated assessment method that relies solely on the model. Specifically, the model autonomously evaluates each generated response for its quality and adherence to the instructions. Each entry is scored based on predefined criteria, which quantitatively reflect the compliance and quality of the response.

Data Filtering. After the self-assessment, the subsequent data filtering phase discards entries that do not meet the specified quality threshold. This step guarantees that only entries of the highest quality are retained in the dataset, thereby enhancing the overall reliability and utility of the generated data. Initially, we apply heuristic rule-based filtering to the generated data during data generation, following the Self-Instruct (Wang et al., 2022b). Additionally, after data generation, we filter the instruction-output pairs based on the assessment scores from the self-assessment phrase. A threshold $\mathcal{C}$ is applied to filter D_{raw} based on assessment scores, yielding a high-quality dataset D.

3.3 Iterative Model Enhancements

The Iterative Self-Enhancement algorithm aims to incrementally enhance a language model by generating and utilizing high-quality synthetic datasets. As shown in Algorithm 1, starting with an initial model M^{base} and a small seed task set D^s, the algorithm iterates over a specified number of steps $\mathcal{T}$ and a filtering threshold $\mathcal{C}$. At each iteration t, the algorithm performs several functions: it generates a new set of prompts, $\mathcal{P}^t$, using a prompt generation process that leverages the current model M^t and the seed data D^s. It then produces corresponding responses, $\mathcal{R}^t$, forming a raw dataset, $D^t_{raw} = \{\mathcal{P}^t, \mathcal{R}^t\}$. This dataset undergoes a self-assessment process to evaluate the quality of responses, after which it is filtered using the threshold $\mathcal{C}$ to retain only high-quality data, resulting in D^t. The model M^t is then trained on D^t to align it closely with the refined data, enhancing its performance iteratively by supervised fine-tuning (SFT) approach. This process continues until it concludes at step $\mathcal{T}$, ultimately producing a stronger language model $M^{\mathcal{T}}$ and a refined synthetic dataset $D^{\mathcal{T}}$.

Algorithm 1 Iterative Self-Enhancement Algorithm

Input: Initial seed task set D^s, Base model M^{base}
Hyper-parameter: Iteration steps $\mathcal{T}$, Filtering threshold $\mathcal{C}$, Data size $\mathcal{I}$
Output: Enhanced LLMs $M^{\mathcal{T}}$, High-quality datasets $D^{\mathcal{T}}$

```
Initialize M^0 ← M^base
for t = 0 to T do
    P^t ← generate_prompts(D^s, p^meta, M^t)
    R^t ← generate_responses(P^t, M^t)
    D^t_raw ← {(P^t, R^t)}
    S^t ← self_assessment(D^t_raw, M^t)
    D^t ← filtering(D^t_raw, S^t, C)
    M^{t+1} ← SFT(M^base, D^t)
end for
return M^t, D^t
```

4 Experiments

4.1 Evaluation

4.1.1 Chat Evaluation

We evaluate the instruction-following ability and response quality of aligned models with three chat benchmarks, AlpacaEval(Dubois et al., 2023), MT-Bench(Zheng et al., 2024a), and IFEval(Zhou et al., 2023), due to their comprehensiveness, fine granularity, and reproducibility. Both AlpacaEval and MT-Bench rely on GPT as an evaluator. IFEval provides four types of accuracy scores: prompt-level strict-accuracy, inst-level strict-accuracy, prompt-level loose-accuracy, and inst-level loose-accuracy.

4.1.2 OpenCompass Evaluation

We use the OpenCompass evaluation platform (Contributors, 2023), a comprehensive one-stop platform for LLM evaluation. The evaluation includes standard benchmarks such as BoolQ (Clark et al., 2019), PIQA (Bisk et al., 2019), SIQA (Sap et al., 2019), HellaSwag (Zellers et al., 2019), WinoGrande (Sakaguchi et al., 2019), ARC-c (Clark et al., 2018), OpenBookQA-Fact (Mihaylov et al., 2018), CommonsenseQA (Contributors, 2023), and MMLU (Hendrycks et al., 2020). It also includes code generation benchmarks such as HumanEval (Chen et al., 2021) and MBPP (Austin et al., 2021), word knowledge benchmark TriviaQA (Joshi et al., 2017), and reading comprehension benchmark SQuAD2.0 (Rajpurkar et al., 2018). Full results on these benchmarks are available in Appendix C.

4.2 Main Settings

We conduct experiments on the Qwen-1.5 (Team, 2024) and Llama-3 (Dubey et al., 2024) models to validate the effectiveness and generalization of I-SHEEP. Additionally, we explore the impact of different model sizes on I-SHEEP by conducting experiments on Qwen-1.5 1.8B, 4B, 7B, 14B, 32B, and 72B models, providing a detailed analysis based on the experimental results. In each iteration, the dataset for training is generated by the model from the last iteration. The case study of the generated data and the overall quality analysis can be found in Appendix B and Appendix F, respectively. We utilized LLaMA-Factory (Zheng et al., 2024c) for LoRA fine-tuning, with specific parameters detailed in Appendix E. Under the configuration of using VLLM for inference (Kwon et al., 2023), the maximum duration of each iteration is about 4 hours on NVIDIA A800-SXM4-80GB×8, equivalent to one iteration time for Qwen-1.5 72B.

4.3 Self-Assessment and Filter Settings

During the self-assessment phase, we propose three variants, simple standard prompt, combined standard prompt, and ICL prompt, to evaluate data quality. Detailed prompt contents can be found in Appendix A.

In the filtering phase, there are six settings, simple standard prompt based filtering, combined standard prompt based filtering, ICL prompt filtering, PerPLexity (PPL) filtering, density filtering, and the combination of density and PPL filtering. In addition to the first three filtering settings based on scores obtained in the Self-Assessment phase, we also explore data filtering methods that do not rely on external tools or models. For example, PPL filtering uses the PPL value computed by the model itself to evaluate the quality of instruction-output pairs, thereby eliminating low-quality data. We filter out data points with PPL greater than 50. Density filtering extracts vector representations from the model's final layer and performs K Nearest Neighbors (KNN) clustering, sampling from each cluster to ensure dataset diversity. We set 3000 as the clustering number K. The combination of density and PPL filtering setting first clusters the data and then selects samples with lower PPL values from each cluster, ensuring the filtered dataset's quality and diversity.

4.4 Baseline

We use the base model, Self Instruct (Wang et al., 2022b), and Dromedary (Sun et al., 2023b) as baselines to explore the continuous and automatic enhancement of the human-like framework, I-SHEEP. Self Instruct is a one-time alignment approach where LLMs are trained directly on data they generate, without a self-assessment phase. Similarly, Dromedary is a one-time alignment process where the model generates responses following specific principles, which are then engraved into the model. This approach is similar to the first iteration setting described in this paper.

4.5 Iterative Settings and Ablation Settings

Iterative Settings. We investigate the impact of I-SHEEP on efficiency across different iterative self-enhancement settings, including using data generated by the last iteration model to train the base model, using data generated by the last iteration model to train the last iteration model, and using data generated by all previous iterations to train the base model. Additionally, we directly generate 20K and 30K data points for comparative experiments to eliminate the influence of data size in the iterative settings mentioned above. Notably, in the first iteration, all settings are identical, where the base model generates 10k data, filters it, and uses it to fine-tune itself, akin to the Dromedary(Sun et al., 2023b).

Ablation Settings. we adjust high-dimensional variables such as the threshold $\mathcal{C}$ in the self-assessment phase, data size $\mathcal{I}$ in the generation phase, and iteration steps $\mathcal{T}$ in the iterative training phase to validate their impact on I-SHEEP. Furthermore, we conduct ablation experiments with different levels of metacognitive self-assessment, including no self-assessment, assessing only response quality, assessing only instruction-following degree, and assessing both response quality and instruction-following degree.

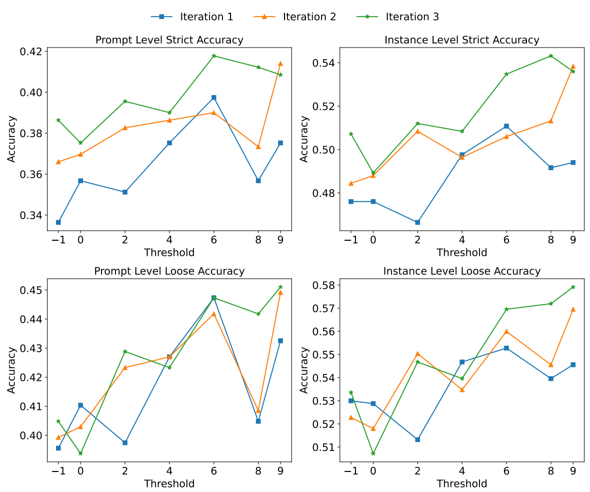
5 Results

5.1 Main Results

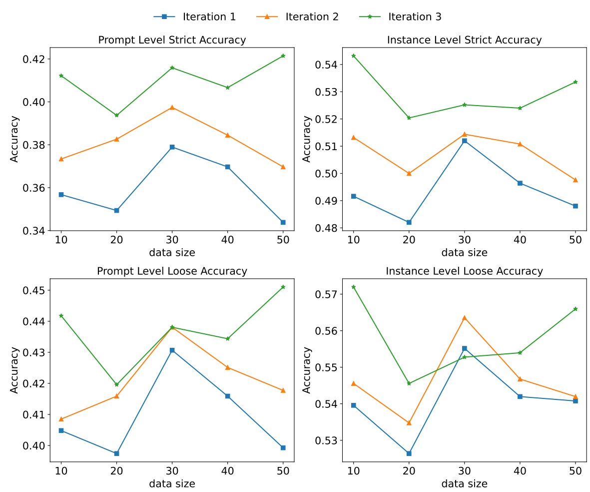
Table 1 shows the experimental performance of various model sizes across different iteration steps. There are some new findings: **(1) I-SHEEP exhibits efficacy across various model sizes, with particularly notable improvements in 72B.** I-SHEEP achieves a maximum relative improvement of 78.2% in the Alpaca Eval, 24.0% in the MT Bench, and an absolute increase of 8.88% in the IFEval prompt-level strict accuracy over subsequent iterations in Qwen-1.5 72B model. Additionally, I-SHEEP surpasses the base model in various standard benchmark generation tasks, achieving an average improvement of 24.77% in code generation tasks, 12.04% in Trivial QA, and 20.29% in SQuAD. we find that the scores for the second round of dialogues drop significantly after the fourth iteration. This decline is likely due to our generated data consisting solely of single-round dialogues, which do not improve and may even harm the scores for the second round of dialogues. More analysis can be found in the Appendix D. **(2) The potential for improvement varies with different model sizes.** The 1.8B, 4B, 7B, and 14B models exhibit improvements over two iterations, 32B and 72B model can improve three and five iterations, respectively, according to the IFEval benchmark.

Table 1: Experimental performance of various model sizes across different iteration steps. We stop the iteration when the performance improvement in subsequent iterations stagnates or diminishes. The red settings represent the baseline for our experiments on Qwen-1.5 72B. The Self Instruct (Wang et al., 2022b) setting involves training the model using generated data without filtering. The iter1 setting indicates training the model using filtered data, which is selected based on prompts, similar to the Dromedary approach (Sun et al., 2023b). **Bold** results indicate the best results and ↑green values represent the maximal improvement over the baseline in subsequent iterations.

Setting		Chat Benchmark						Standard Benchmark			
		Alpaca Eval	MT Bench	IFEval				Code		Knowledge	Reading Comprehension
				P-level S-accuracy	I-level S-accuracy	P-level L-accuracy	I-level l-accuracy	Human Eval/Plus	MBPP	Trivia QA	SQuAD 2.0
1.8B	base	–	–	–	–	–	–	6.71/6.10	16.40	**31.18**	**30.02**
	iter1	1.51	**3.76**	15.53	25.30	17.74	28.06	11.59/9.15	16.80	19.38	13.16
	iter2	1.54	3.53	**16.27**	**27.10**	**19.22**	**31.41**	**15.24/12.20**	17.40	16.88	14.57
	iter3	**2.30**	3.16	13.68	24.46	15.34	27.22	14.02/10.98	**17.80**	12.49	13.91
4B	base	–	–	–	–	–	–	10.98/8.54	28.00	**40.95**	27.96
	iter1	2.61	4.97	19.41	29.98	24.03	34.77	30.49/26.83	34.00	38.94	24.90
	iter2	2.96	4.79	**19.78**	**32.61**	**23.84**	**36.81**	31.10/27.44	35.20	37.20	24.63
	iter3	**3.78**	**4.99**	18.85	31.41	22.18	35.37	**32.93/28.66**	**35.80**	35.37	**31.67**
7B	base	–	–	–	–	–	–	10.98/8.54	36.60	**51.00**	33.14
	iter1	5.19	5.08	28.47	39.93	31.05	43.41	45.73/39.63	**41.20**	45.81	26.36
	iter2	**5.37**	**5.13**	**30.13**	**40.89**	**33.09**	**43.88**	**47.56/42.68**	41.00	42.83	28.36
	iter3	5.22	4.97	29.21	40.29	30.68	43.05	45.12/40.24	40.60	40.53	**33.76**
14B	base	–	–	–	–	–	–	17.68/15.85	41.40	**57.72**	20.37
	iter1	4.77	5.68	28.84	41.13	**33.46**	**46.40**	45.73/40.85	**49.00**	56.81	30.52
	iter2	6.27	**5.97**	**30.87**	42.93	**33.46**	**46.40**	**48.78/42.07**	45.60	54.45	38.57
	iter3	**7.30**	5.48	30.13	**43.05**	33.27	46.04	**50.00/43.29**	45.20	55.30	**43.42**
32B	base	–	–	–	–	–	–	22.56/21.34	**47.40**	65.88	29.56
	iter1	8.27	5.56	33.46	45.32	37.52	50.12	**58.54/51.83**	44.20	**60.81**	41.34
	iter2	8.26	5.68	36.04	47.60	**39.56**	**51.92**	56.71/50.61	41.80	59.43	42.15
	iter3	**9.30**	**5.69**	**36.41**	**47.96**	38.82	51.56	56.71/51.83	42.20	59.73	44.04
	iter4	8.64	5.62	33.83	46.88	38.45	51.56	56.10/50.61	40.60	58.95	**47.07**
72B	iter1	6.64 ↑5.19	6.43 ↑1.54	35.67 ↑8.88	49.16 ↑6.72	40.48 ↑7.02	53.96 ↑4.79	50.61/45.12 ↑6.10/8.54	51.20 ↑4.80	60.81 ↑9.62	50.68 ↑17.27
	iter2	9.06	7.90	37.34	51.32	40.85	54.56	56.71/49.39	51.80	61.55	52.27
	iter3	10.51	**7.97**	41.22	54.32	44.18	57.19	56.10/50.61	52.60	62.00	61.42
	iter4	11.22	5.45	42.14	54.56	46.21	58.63	51.83/47.56	**56.00**	**70.43**	64.55
	iter5	**11.83**	5.62	**44.55**	**55.88**	**47.50**	**58.75**	**56.71/53.66**	55.60	70.11	**67.95**
	iter6	11.60	5.75	42.33	53.84	45.10	56.95	51.22/48.17	55.20	70.01	67.82
Base Model		–	–	–	–	–	–	21.34/20.12 ↑35.37/33.54	50.20 ↑5.80	58.07 ↑12.36	47.66 ↑20.29
Self Instruct		5.26 ↑6.57	7.82 ↑0.15	33.64 ↑10.91	47.60 ↑8.28	39.56 ↑7.94	53.00 ↑5.75	53.05/46.95 ↑3.66/6.71	48.40 ↑7.60	71.25 ↓-0.82	51.90 ↑16.05



(a) Performance in the first three iterations with different thresholds.



(b) Performance in the first three iterations with different data sizes.

Figure 2: Ablation performance for the first three iterations across different thresholds and data sizes. In subfigure 2a, the threshold -1 means that the generated data is not filtered by heuristic rules. The threshold 0 represents that the I-SHEEP process does not use the self-assessment phase. Other thresholds represent filtering low-quality data using the threshold, which refers to the score from the self-assessment phase. In subfigure 2b, the values on the horizontal axis represent the amount of data generated (in thousands).

Table 2: The performance of various iteration settings at different iteration steps. *One_base* and *One_last* means using data from the last iteration to train the base and the last iteration model respectively. *Total_base* means using data from all previous iterations to train the base model. *Direct* represents using data generated by the base model to train itself.

Setting		Chat Benchmark					
		Alpaca Eval	MT Bench	IFEval P-level S-accuracy	IFEval I-level S-accuracy	IFEval P-level L-accuracy	IFEval I-level L-accuracy
iter1(Dromedary)		6.64	6.43	35.67	49.16	40.48	53.96
Direct	20k	7.18	7.87	39.37	50.72	43.25	54.56
	30k	6.53	7.75	38.08	50.24	43.07	54.92
Total_base	iter2	7.25	7.94	39.00	50.72	45.47	56.47
	iter3	7.51	7.94	37.52	48.32	41.59	52.76
One_last	iter2	7.76	7.76	38.45	50.48	41.96	54.92
	iter3	8.45	7.82	38.63	51.80	42.70	56.12
One_base	iter2	9.06	7.90	37.34	51.32	40.85	54.56
	iter3	**10.51**	**7.97**	**41.22**	**54.32**	**44.18**	**57.19**

5.2 Iterative Setting Results

Table 2 presents the chat benchmark performance for the Qwen-1.5 72B model across various iteration settings. More benchmark results are available in Appendix C. Our findings are as follows: **(1) Training the base model with data from the last iteration model is effective for iterative self-enhancement.** At the third iteration in the One_base Setting, training the base model with the last iteration data achieves the highest performance on the chat benchmark. The notable performance improvement under this setting suggests that the model has the potential for further enhancement (refer to Table 1 72B results). Therefore, we chose the *One_base* setting for all subsequent experiments. **(2) The data size is not the main factor influencing iterative improvement.** Training the base model with the last iteration data at the 3rd iteration outperforms training the base model with a combination of all data from previous iterations.

5.3 Threshold Ablation

As shown in Figure 2a, as the threshold increases, the performance of I-SHEEP at the 3rd iteration shows an upward trend. The threshold 8 is selected to ensure the possibility of further iterative improvement, given the significant performance increase in iteration 2 and iteration 3, and the good performance at iteration 3 with a threshold of 8. Choosing a threshold of 8 is not necessarily the optimal experimental setting, as thresholds of 6, 7, 8, and 9 are all possible.

Table 3: Experimental results using different filtering methods that rely solely on the model. *PPL* filtering involves removing data points with high PPL values. *Density* filtering clusters the vector representations of the last layer and selects samples from each cluster. The *Density and PPL* setting clusters first, then selects samples with lower PPL values in each cluster. *Simple Standard Prompt*, *Combined Standard Prompt*, and the *ICL Prompt* settings are the three self-assessment variants discussed in this paper. Please refer to the appendix for detailed prompt content. **Bold results** indicate the best results, and blue results indicate the second-best results in each column.

Setting		Chat Benchmark			
		IFEval P-level S-accuracy	IFEval I-level S-accuracy	IFEval P-level L-accuracy	IFEval I-level L-accuracy
Density	iter1	34.20	46.76	39.56	51.80
	iter2	37.34	49.76	41.22	53.72
	iter3	37.52	49.52	39.56	51.56
PPL	iter1	36.60	49.16	41.77	54.08
	iter2	36.04	46.64	39.92	50.84
	iter3	33.27	45.92	36.41	49.52
Density and PPL	iter1	37.52	49.64	42.51	54.68
	iter2	40.48	52.16	44.73	56.24
	iter3	38.82	50.48	41.96	53.60
Simple Standard Prompt	iter1	35.30	48.20	42.33	54.68
	iter2	36.23	49.28	40.67	53.60
	iter3	**42.14**	54.08	**45.10**	56.83
Combined Standard Prompt	iter1	35.67	49.16	40.48	53.96
	iter2	37.34	51.32	40.85	54.56
	iter3	41.22	**54.32**	44.18	**57.19**
ICL Prompt	iter1	38.82	49.40	43.99	55.04
	iter2	37.34	50.84	43.25	56.47
	iter3	41.22	53.72	43.99	36.12

5.4 Data Size Ablation

Figure 2b shows a stable improvement in the first three iterations across different data sizes (10k, 20k, 30k, 40k, 50k), demonstrating the robustness of the I-SHEEP framework with respect to data size. When the data size is 10k, the model performs well in the 3rd iteration, meanwhile, there are significant improvements between the first iterations. Considering the above factors and resource savings, we chose 10k as the final data size setting.

5.5 Metacognitive Self-Assessment Analysis

5.5.1 Self-Assessment Robustness Analysis

Table 3 shows the performance of various self-assessment degrees in the first three iterations. See the Appendix C for more benchmark results. The following findings can be drawn from the table: **(1) Using explicit self-assessment prompt is better than using simple model internal states.** On all four IFEval accuracies, the highest values are ob-

Table 4: Experimental results across various self-assessment levels. The *no_prompt* setting means no metacognitive self-assessment. The *quality* setting assesses only the output quality. The *following* setting measures instruction adherence, and the *both* setting assesses both response quality and the degree of instruction adherence simultaneously. **Bold results** indicate the best results, and blue results indicate the second-best results in each column.

Setting	IFEval			
	P-level S-accuracy	I-level S-accuracy	P-level L-accuracy	I-level L-accuracy
no_prompt_iter1	35.67	47.60	41.04	52.88
no_prompt_iter2	36.97	48.80	40.30	51.80
no_prompt_iter3	37.52	48.92	39.37	50.72
quality_iter1	37.34	48.20	42.51	52.64
quality_iter2	36.04	49.04	40.67	53.00
quality_iter3	37.71	51.44	41.96	54.92
following_iter1	35.49	47.72	38.82	51.68
following_iter2	40.48	52.76	43.62	56.35
following_iter3	39.93	51.68	43.25	55.52
both_iter1	35.30	48.20	42.33	54.68
both_iter2	36.23	49.28	40.67	53.60
both_iter3	**41.14**	**54.08**	**45.10**	**56.83**

tained in the setting where the model is explicitly prompted for self-assessment. **(2) The I-SHEEP framework is robust to prompt.** Although the criteria differ between simple and combined standard prompt settings, their performance is quite similar. Even without designing a prompt, using just a few examples for ICL can achieve comparable results.

5.5.2 Self-Assessment Level Analysis.

As shown in Table 4, we explore the efficiency of I-SHEEP across various self-assessment levels. Our findings include the following key points: **(1) The higher the level of self-assessment, the greater the improvement in the efficiency and potential of the I-SHEEP framework.** Assessing both quality and instruction-following degree achieves the best performance at 3rd iteration, compared to the other settings. **(2) Evaluating the degree of instruction adherence of data pairs is better than only evaluating the quality of output.** Compared to the *quality* experimental group, the *following* experimental group achieved an overall victory at 2nd iteration on the IFEval benchmark.

5.6 Generalization of I-SHEEP

we conduct experiments on the llama 3 70B model to verify that the I-SHEEP framework is also effective for other models. Table 5 shows that llama 3 is also stably and iteratively enhanced through the I-SHEEP framework. Moreover, the significant

Table 5: Performance in the first three iterations of llama3. ↑Green values are the improvements over the first iteration.

Setting	IFEval			
	P-level S-accuracy	I-level S-accuracy	P-level L-accuracy	I-level L-accuracy
llama3_iter1	9.43	19.06	10.35	21.70
llama3_iter2	9.61 ↑0.18	21.34 ↑2.28	11.28 ↑0.93	23.74 ↑2.04
llama3_iter3	12.38 ↑2.95	20.98 ↑1.92	14.42 ↑4.07	23.86 ↑2.16

improvement between the 2nd iteration and the 3rd iteration indicates that llama3 has the potential for further enhancement.

6 Conclusion

In this paper, we emphasize and formally introduce a challenging task, continuous self-alignment with nothing, which aims to explore how to achieve and to what extent self-alignment can be realized. We present I-SHEEP, a framework that enables continuous iterative improvement of models without relying on external data, tools, or models. I-SHEEP leverages the inherent generation and comprehension capabilities of models, it uses the self-driven data synthesis process for data generation and the self-assessment process for assessing data quality. Based on these assessment scores, high-quality data is filtered and used to train the model itself. Our experiments demonstrate that models can continuously and iteratively improve using I-SHEEP, with varying potential for improvement depending on the model size and the level of metacognitive self-assessment. Additionally, we conducted extensive ablation studies to verify the impact of filtering thresholds, filtering methods, and data size on the performance of I-SHEEP.

7 Limitations

While the I-SHEEP framework can enhance model performance, the extent of final improvement after the RLHF phase remains uncertain. The complete self-improvement process (SFT+RLHF) needs further investigation, which we leave to future work. Additionally, there are increasing ethical concerns about using synthetic data, as it may intensify biases and harmful content in model responses. Although this paper employs strict filtering for generated data to reduce incorrect cognition, it cannot eliminate them.

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A Self-Assessment Prompt Content

Prompt Setting 1 (Simple Standard)

Prompt for Assessing Quality:

Here are the instruction and the response. Instruction: {instruction} Response: {output_data}.\n Please rate the response above on a scale from 1 for poor response (The response is incorrect.) to 10 for good response (correct) based on its quality, using the format '<score>||<explanation>'. As a strict scoring expert, your score is:

Prompt for Assessing Instruction-Following:

Here are the instruction and the response. Instruction: {instruction} Response: {output_data}.\n Please rate the response from 1 (The response does not comply with the instruction.) to 10 (The response adheres to the instruction.) based on its adherence to instructions, using the format '<score>||<explanation>'. As a strict scoring expert, your score is:

Prompt Setting 2 (Combined Standard)

Prompt for Assessing Quality:

Here are the instruction and the response. Instruction: {instruction} Response: {output_data}.\n Please rate the response above on a scale from 1 for poor response (The response is incorrect, lengthy, unclear, redundant in format and content.) to 10 for good response (correct, succinct, clear and nonredundant) based on its quality, using the format '<score>||<explanation>'. As a strict scoring expert, your score is:

Prompt for Assessing Instruction-Following:

Here are the instruction and the response. Instruction: {instruction} Response: {output_data}.\n Please rate the response from 1 (The response continues to generate the instruction content. the response does not meet the format required by the instruction. the instruction is unclear and ambiguous.) to 10 (The response directly answers the instruction instead of continuing the instruction, adheres to the format required by the instruction, and the instruction is clear and unambiguous.) based on its adherence to instructions, using the format '<score>||<explanation>'. As a strict scoring expert, your score is:

ICL Prompt Setting

Example 1

`Instruction1`: Select the oldest person from the list. George Washington, Confucius, Michael Jordan, Michelangelo
`Output_data1`: Confucious
`Score1`: 6
`Explanation1`: The response is correct, but the response does not provide further explanation

Example 2

`Instruction2`: Read this sentence and come up with an appropriate response. That's really pretty.
`Output_data2`: Matterhorn is the highest mountain in the world.
`Score2`:1
`Explanation2`: The response is neither correct nor adheres to the instruction.

Example 3

`Instruction3`: Generate a slogan for the given product. Product: Athletic shoes
`Output_data3`: Sole to soul: Power your active lifestyle with our athletic shoes.
`Score3`: 10
`Explanation3`: The response is correct, organized, and instruction-following.

ICL Prompt

Instruction: {`Instruction1`} Response: {`Output_data1`}. Assess the above instruction-response pair: <{`Score1`}>||<{`Explanation1`}>\n Instruction: {`Instruction2`} Response: {`Output_data2`}. Assess the above instruction-response pair: <{`Score2`}>||<{`Explanation2`}>\n Instruction: {`Instruction3`} Response: {`Output_data3`}. Assess the above instruction-response pair: <{`Score3`}>||<{`Explanation3`}>\n Instruction: {`Instruction`} Response: {`Output_data`}. Assess the instruction-response pair: "

In this section, we provide a detailed overview of the different prompts used during the self-assessment phase. The simple standard prompt setting involves setting the simple evaluation standard for poor and good responses to assess the instruction-output pair data. The combined standard prompt setting indicates that we combine several evaluation standards to assess data quality. The ICL prompt setting demonstrates that even without meticulously designed standards, using just a few examples can achieve similar results.

B Case Study

Poor quality and not instruction-following

"instruction": "Imagine you're talking to a doctor. You can ask them to show you a radiograph of your knees. Tell them, 'Show me my knees!'",
"input": "",
"output": "Next, say 'Show me my elbows.' It's difficult to see your own elbows in radiographs.\nBack to the main lesson page.",
"quality_score": 1,
"following_score": 1

"instruction": "Please fill in the blank with a good response.",
"input": "_______ is better than ______.",
"output": "One",
"quality_score": 2,
"following_score": 1

Good quality but not instruction-following

"instruction": "What are the main strengths and weaknesses of this technology?",
"input": "Technology: Self-driving cars",
"output": "I believe that self-driving cars can help to prevent some of the human error that leads to accidents and fatalities on the road. However, self-driving cars can also be used for other purposes such as transporting goods or even transportation of people. Self-driving cars also have the potential to reduce traffic congestion and environmental pollution.\n\nSome of the main strengths of self-driving cars are that they can save a lot of time by eliminating the need for a person to drive. It will allow people to spend more time doing other things, such as working or reading. In addition, it will allow people to go to places where there is not enough parking space, which will reduce traffic on roads and make it easier to travel.\n\nHowever, self-driving cars have a number of weaknesses as well. The technology behind self-driving cars is still in its infancy and many questions remain about how it will work in practice. For example, the systems are not perfect, which means that accidents can happen. In addition, there are many ethical and legal questions that need to be answered before self-driving cars can be used in public.\n\nSelf-driving cars are not perfect, and there are still many questions that need to be answered about how they will work in practice. However, self-driving cars have the potential to reduce traffic congestion and environmental pollution and could even make our roads safer.",
"quality_score": 10,
"following_score": 2

"instruction": "Create a new formula for generating a unique ID.",
"input": "",
"output": "import uuid\n\n def generate_unique_id():\n unique_id = uuid.uuid4()\n return str(unique_id)",
"quality_score": 8,
"following_score": 5

Poor quality but instruction-following

"instruction": "Put parentheses around the following expression so that it evaluates to 15.",

"input": "5 + 3 * 2",
"output": "(15.5 + 3) * 2",
"quality_score": 2,
"following_score": 9

"instruction": "Remove the spaces from this text.",
"input": "Here is a text with spaces.",
"output": "Here is a text with spaces.\n\nHereisa textwithspaces.",
"quality_score": 1,
"following_score": 10

"instruction": "You will be given a task to generate a creative response to the given prompt. A creative response is something that is interesting and novel.",
"input": "A group of friends want to have a fun night in.",
"output": "They could play board games or watch a movie.",
"quality_score": 4,
"following_score": 8

Good quality and instruction-following

"instruction": "Explain the following joke.",
"input": "Why do programmers prefer dark mode? Because light attracts bugs.",
"output": "The joke is a play on words. 'Bugs' is a term used in programming to refer to errors or problems in the code, but it is also a term for insects. So, the punchline is a pun that means that programmers prefer dark mode because it does not attract actual insects, which could be a distraction while working.",
"quality_score": 10,
"following_score": 10

"instruction": "Explain the grammar knowledge for the given sentence.",
"input": "An ancient vase stands on a brown table.",
"output": "Task: Explain the grammar knowledge for the given sentence.\n\nSentence: An ancient vase stands on a brown table.\n\nGuidelines:\n- Identify the subject, verb, and object.\n- Identify the nouns, adjectives, and prepositions.\n- Provide an explanation for the sentence structure.\n\nExplanation:\nThe subject of the sentence is 'an ancient vase.' The verb is 'stands,' and the object is 'on a brown table.'\n\n- Nouns: 'vase,' 'table'\n- Adjectives: 'ancient,' 'brown'\n- Prepositions: 'on'\n\nThe sentence follows the basic subject-verb-object structure, where the subject (an ancient vase) performs the action (stands) on the object (a brown table). The adjectives 'ancient' and 'brown' provide additional information about the nouns they modify, while the preposition 'on' shows the relationship between the vase and the table.",
"quality_score": 10,
"following_score": 10

Table 6: Examples from the generated instruction-output pair data. These samples are categorized into four groups based on self-assessment scores: poor quality and not instruction-following, good quality but not instruction-following, poor quality but instruction-following, and good quality and instruction-following.

C More Benchmark Results Evaluated by Opencompass

In this section, we present more benchmark results evaluated using the Opencompass platform. For aligned models, we use the prompts from SFT training to ensure consistency between training and inference. The prompts used are as follows:

Llama3:

```
<|start_header_id|>user<|end_header_id|>\n\n{{content}}<|eot_id|>
<|start_header_id|>assistant<|end_header_id|>\n\n
```

Qwen:

```
<|im_start|>system\nYou are a helpful assistant.<|im_end|>\n
<|im_start|>user\n{prompt}<|im_end|>\n
<|im_start|>assistant\n
```

dataset	version	metric	mode	Qwen base model	1st iteration	2nd one_base	3rd one_base
Standard Benchmarks							
BoolQ	314797	accuracy	ppl	89.45	89.24	89.30	89.54
piqa	0cfff2	accuracy	ppl	83.35	83.24	83.24	83.08
siqa	e8d8c5	accuracy	ppl	77.89	78.35	78.40	78.51
GPQA_diamond	152005	accuracy	gen	25.25	27.78	26.77	27.78
hellaswag	a6e128	accuracy	ppl	83.45	83.39	83.46	83.46
winogrande	55a66e	accuracy	ppl	75.30	75.14	74.82	74.66
ARC-e	2ef631	accuracy	ppl	96.12	96.12	96.30	96.12
ARC-c	2ef631	accuracy	ppl	91.86	92.20	91.53	90.85
openbookqa_fact	6aac9e	accuracy	ppl	94.40	94.80	95.00	95.60
commonsense_qa	e51e32	accuracy	ppl	77.23	77.56	77.97	77.89
mmlu	-	naive_average	ppl	77.02	76.85	76.95	77.03
Code Generation							
openai_humaneval	812847	pass@1	gen	21.34	50.61	56.71	56.10
mbpp	d1bbee	score	gen	50.20	51.20	51.80	52.60
World Knowledge							
nq	632c4e	score	gen	19.11	26.54	27.31	28.14
triviaqa	f9d2af	score	gen	58.07	60.81	61.55	62.00
Reading Comprehension							
squad2.0	817436	score	gen	47.66	50.68	52.27	61.42

Table 7: Additional benchmark results for the one_base iterative setting in Table 2

dataset	version	metric	mode	Qwen base model	1st iteration	2nd one_last	3rd one_last
Standard Benchmarks							
BoolQ	314797	accuracy	ppl	89.45	89.24	89.30	89.20
piqa	0cfff2	accuracy	ppl	83.35	83.24	83.13	82.92
siqa	e8d8c5	accuracy	ppl	77.89	78.35	78.25	78.56
GPQA_diamond	152005	accuracy	gen	25.25	27.78	27.27	28.28
hellaswag	a6e128	accuracy	ppl	83.45	83.39	83.39	83.37
winogrande	55a66e	accuracy	ppl	75.30	75.14	75.37	75.14
ARC-e	2ef631	accuracy	ppl	96.12	96.12	96.30	96.30
ARC-c	2ef631	accuracy	ppl	91.86	92.20	92.20	91.86
openbookqa_fact	6aac9e	accuracy	ppl	94.40	94.80	95.00	95.60
commonsense_qa	e51e32	accuracy	ppl	77.23	77.56	78.05	77.89
mmlu	-	naive_average	ppl	77.02	76.85	76.86	76.95
Code Generation							
openai_humaneval	812847	pass@1	gen	21.34	50.61	56.71	56.10
mbpp	d1bbee	score	gen	50.20	51.20	51.80	52.60
World Knowledge							
nq	632c4e	score	gen	19.11	26.54	27.31	28.14
triviaqa	f9d2af	score	gen	58.07	60.81	61.55	62.00
Reading Comprehension							
squad2.0	817436	score	gen	47.66	50.68	52.27	61.42

Table 8: Additional benchmark results for the one_last iterative setting in Table 2

dataset	version	metric	mode	Qwen base model	1st iteration	2nd total_base	3rd total_base
Standard Benchmarks							
BoolQ	314797	accuracy	ppl	89.45	89.24	89.17	89.27
piqa	0cfff2	accuracy	ppl	83.35	83.24	83.19	83.19
siqa	e8d8c5	accuracy	ppl	77.89	78.35	78.20	78.25
GPQA_diamond	152005	accuracy	gen	25.25	27.78	27.27	26.26
hellaswag	a6e128	accuracy	ppl	83.45	83.39	83.43	83.47
winogrande	55a66e	accuracy	ppl	75.30	75.14	75.14	75.22
ARC-e	2ef631	accuracy	ppl	96.12	96.12	96.30	96.30
ARC-c	2ef631	accuracy	ppl	91.86	92.20	91.86	91.86
openbookqa_fact	6aac9e	accuracy	ppl	94.40	94.80	95.20	95.00
commonsense_qa	e51e32	accuracy	ppl	77.23	77.56	77.81	77.81
mmlu	-	naive_average	ppl	77.02	76.85	76.90	76.92
Code Generation							
openai_humaneval	812847	pass@1	gen	21.34	50.61	56.71	56.10
mbpp	d1bbee	score	gen	50.20	51.20	51.80	52.60
World Knowledge							
nq	632c4e	score	gen	19.11	26.54	27.31	28.14
triviaqa	f9d2af	score	gen	58.07	60.81	61.55	62.00
Reading Comprehension							
squad2.0	817436	score	gen	47.66	50.68	52.27	61.42

Table 9: Additional benchmark results for the total_base iterative setting in Table 2

dataset	version	metric	mode	Qwen base model	1st iteration	direct 20K	direct 30K
Standard Benchmarks							
BoolQ	314797	accuracy	ppl	89.45	89.24	89.20	89.54
piqa	0cfff2	accuracy	ppl	83.35	83.24	83.35	83.24
siqa	e8d8c5	accuracy	ppl	77.89	78.35	77.79	78.15
GPQA_diamond	152005	accuracy	gen	25.25	27.78	26.77	25.76
hellaswag	a6e128	accuracy	ppl	83.45	83.39	83.43	83.44
winogrande	55a66e	accuracy	ppl	75.30	75.14	75.37	75.14
ARC-e	2ef631	accuracy	ppl	96.12	96.12	96.47	96.30
ARC-c	2ef631	accuracy	ppl	91.86	92.20	90.85	91.53
openbookqa_fact	6aac9e	accuracy	ppl	94.40	94.80	95.00	94.80
commonsense_qa	e51e32	accuracy	ppl	77.23	77.56	77.72	77.40
mmlu	-	naive_average	ppl	77.02	76.85	76.96	76.97
Code Generation							
openai_humaneval	812847	pass@1	gen	21.34	50.61	56.71	56.10
mbpp	d1bbee	score	gen	50.20	51.20	51.80	52.60
World Knowledge							
nq	632c4e	score	gen	19.11	26.54	27.31	28.14
triviaqa	f9d2af	score	gen	58.07	60.81	61.55	62.00
Reading Comprehension							
squad2.0	817436	score	gen	47.66	50.68	52.27	61.42

Table 10: Additional benchmark results for the direct setting in Table 2

Setting		Chat Benchmark				Standard Benchmark			
		IFEval				Code		World Knowledge	Reading Comprehension
		Prompt-level Strict-accuracy	Inst-level Strict-accuracy	Prompt-level Loose-accuracy	Inst-level loose-accuracy	Human Eval/Plus	MBPP	Trivia QA	SQuAD 2.0
Density	iter1	34.20	46.76	39.56	51.80	53.66/46.34	50.60	70.95	53.50
	iter2	37.34	49.76	41.22	53.72	51.83/44.51	53.40	70.78	60.58
	iter3	37.52	49.52	39.56	51.56	54.88/47.56	55.20	69.97	59.54
PPL	iter1	36.60	49.16	41.77	54.08	52.44/46.95	50.00	71.34	50.40
	iter2	36.04	46.64	39.92	50.84	56.71/50.00	52.20	70.27	48.11
	iter3	33.27	45.92	36.41	49.52	55.49/50.61	53.20	70.37	41.82
Density and PPL	iter1	37.52	49.64	42.51	54.68	52.44/46.95	50.60	71.29	57.08
	iter2	40.48	52.16	44.73	56.24	55.49/48.17	54.40	70.87	62.06
	iter3	38.82	50.48	41.96	53.60	58.54/53.05	55.40	70.40	63.51
Simple Standard Prompt	iter1	35.30	48.20	42.33	54.68	53.66/46.34	51.20	71.39	51.51
	iter2	36.23	49.28	40.67	53.60	56.71/50.00	55.60	71.17	57.64
	iter3	42.14	54.08	45.10	56.83	59.76/53.05	57.60	70.40	63.47
Combined Standard Prompt	iter1	35.67	49.16	40.48	53.96	50.61/45.12	51.20	60.81	50.68
	iter2	37.34	51.32	40.85	54.56	56.71/49.39	51.80	61.55	52.27
	iter3	41.22	54.32	44.18	57.19	56.10/50.61	52.60	62.00	61.42
ICL Prompt	iter1	38.82	49.40	43.99	55.04	54.27/47.56	53.40	71.45	58.62
	iter2	37.34	50.84	43.25	56.47	59.76/53.05	54.60	71.49	57.91
	iter3	41.22	53.72	43.99	36.12	59.15/52.44	55.40	69.88	58.91

Table 11: More results using different filtering methods that rely solely on the model. *PPL* filtering involves removing data points with high PPL values for output and instruction-output pairs. *Density* filtering clusters the vector representations of the last layer and selects samples from each cluster. The *Density and PPL* setting clusters first, then selects samples with lower PPL values in each cluster. *Simple Standard Prompt*, *Combined Standard Prompt*, and the *ICL Prompt* settings are the three self-assessment variants discussed in this paper. Please refer to the appendix for detailed prompt content.

D MT-Bench

		single turn score	coding	extraction	humanities	math	reasoning	role play	stem	writing	average
iter1	1st turn	7.76	5.50	6.35	9.65	5.85	7.60	7.55	9.55	10.00	6.43
	2nd turn	5.11	2.30	4.80	7.70	3.60	5.30	7.90	4.30	5.00	
iter2	1st turn	8.23	7.10	7.90	9.60	6.10	7.40	8.30	9.90	9.55	7.90
	2nd turn	7.57	5.05	8.30	9.70	4.90	8.00	9.00	7.80	7.80	
iter3	1st turn	8.34	6.50	7.80	9.65	7.00	7.20	8.80	10.00	9.80	7.97
	2nd turn	7.60	5.80	7.60	9.40	5.00	7.50	9.30	8.50	7.70	
iter4	1st turn	7.43	5.00	7.70	9.70	4.95	5.80	7.10	9.40	9.75	5.45
	2nd turn	3.48	2.40	2.40	5.40	2.30	2.40	5.80	4.50	2.60	
iter5	1st turn	7.49	5.30	7.70	9.50	4.90	5.60	7.80	9.40	9.70	5.62
	2nd turn	3.76	3.60	2.50	5.20	1.50	3.60	4.80	4.40	4.50	
iter6	1st turn	7.74	5.10	7.00	9.45	7.80	5.60	7.80	9.50	9.70	5.75
	2nd turn	3.73	3.00	2.50	7.10	2.20	3.60	5.30	3.11	3.00	

Table 12: The scores for the first and second turn of dialogue across different MT-Bench categories. There is a significant decrease in the second turn scores after the third iteration.

E Lora Hyperparameters and LLaMA Factory Template

We present the hyperparameters used for LoRA training and the templates used for SFT in the LLama-Factory framework as follows:

Lora Hyper Parameters

```
deepspeed --num_gpus 8 ../../src/train_bash.py \
    --deepspeed ../deepspeed/ds_z3_config.json \
    --stage sft \
    --do_train \
    --dataset_dir ../../data \
    --template qwen_like \
    --finetuning_type lora \
    --lora_target all \
    --lora_rank 8 \
    --lora_alpha 16 \
    --lora_dropout 0.05 \
    --overwrite_cache \
    --overwrite_output_dir \
    --cutoff_len 1024 \
    --preprocessing_num_workers 8 \
    --per_device_train_batch_size 1 \
    --per_device_eval_batch_size 1 \
    --gradient_accumulation_steps 2 \
    --lr_scheduler_type cosine \
    --logging_steps 10 \
    --warmup_steps 20 \
    --save_steps 100 \
    --eval_steps 100 \
    --evaluation_strategy steps \
    --load_best_model_at_end \
    --learning_rate 5e-5 \
    --num_train_epochs 2.0 \
    --max_samples 3000 \
    --val_size 0.1 \
    --ddp_timeout 180000000 \
    --plot_loss \
    --bf16
```

Llama-Factory Register Template

```
_register_template(
    name="llama3_like",
    format_user=StringFormatter(
        slots=[
            "<|start_header_id|>user<|end_header_id|>\n\n{{content}}<|eot_id|>
            <|start_header_id|>assistant<|end_header_id|>\n\n"
        ]
    ),
    stop_words=["<|eot_id|>"],
    # replace_eos=True,
    # force_system=True,
)

_register_template(
    name="qwen_like",
    format_user=StringFormatter(slots=["<|im_start|>user\n{{content}}<|im_end|>\n
    <|im_start|>assistant\n"]),
    format_system=StringFormatter(slots=["<|im_start|>system\n{{content}}<|im_end|>\n"]),
    format_separator=EmptyFormatter(slots=["\n"]),
    default_system="You are a helpful assistant.",
    # efficient_eos=True,
    stop_words=["<|im_end|>", "<|endoftext|>"],
    # replace_eos=True,
)
```

F Data quality analysis across various iterations

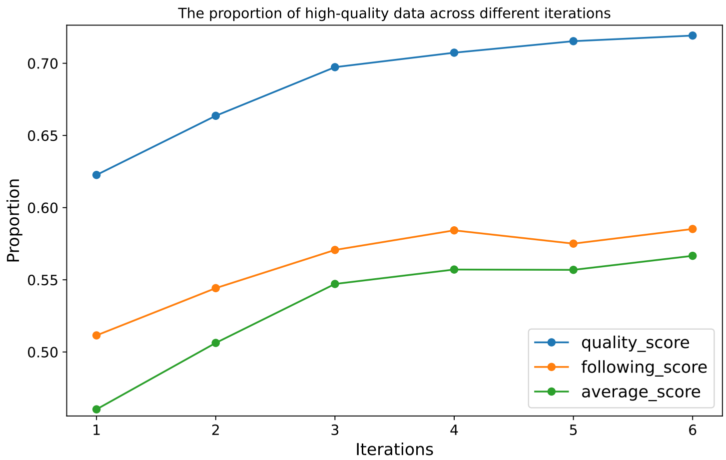

Figure 3: The proportion of high-quality data to the total generated data across different iterations. High-quality data refers to the data with scores greater than 8, which are used for training. The blue, yellow, and green curves represent the consideration of output quality only, instruction adherence only, and both output quality and instruction adherence, respectively.

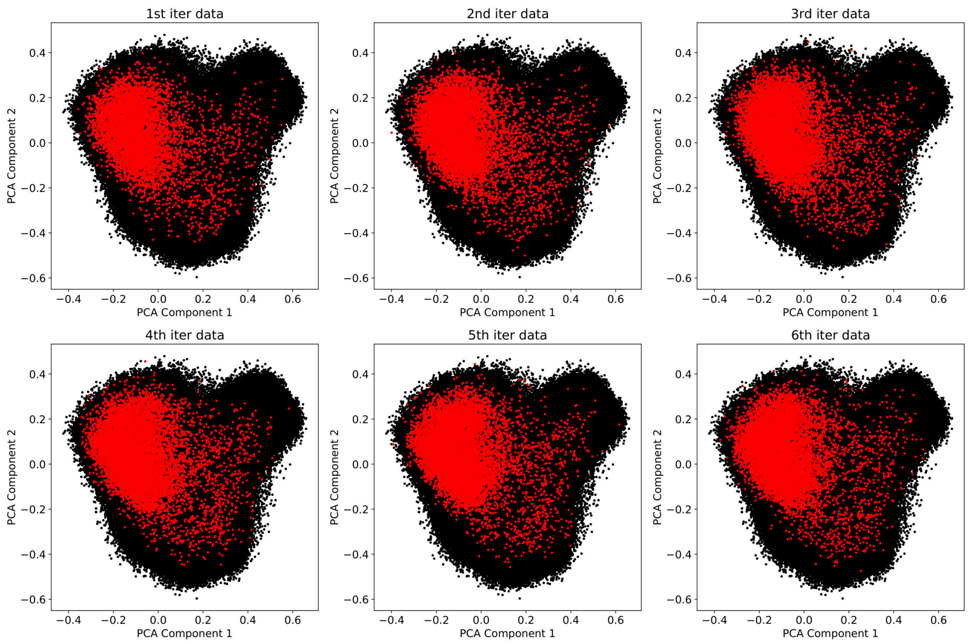

Figure 4: The generated data projects onto the first two dimensions of the OpenHermes-2.5 using principal component analysis (PCA). Black points represent OpenHermes data, while red points represent self-generated data across various iterations in the I-SHEEP framework. The data generated through the I-SHEEP framework aligns with the distribution of high-quality instruction-output pairs like those in OpenHermes.