Unlocking LLMs' Self-Improvement Capacity with Autonomous Learning for Domain Adaptation

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Abstract

Self-supervised pre-training and instruction fine-tuning demonstrate the potential of large language models (LLMs) for domain adaptation (DA). In pursuit of superhuman performance, LLMs have demonstrated significant potential in math and coding through self-improvement algorithms that rely on iterative training with self-generated data. This success stems from the clear reward signals in these environments, which provide a solid foundation for self-improvement. However, when it comes to general DA scenarios, two main challenges emerge: 1) ambiguous self-improvement reward signals and 2) lack of high-quality instruction fine-tuning datasets. This motivates this paper addresses how LLMs can adapt autonomously to new domains using only a large amount of unlabeled target corpora. Inspired by the human practice of self-reflection through open- and closed-book exercises to achieve domain generalization, we propose autonomous learning, which creates a self-improvement learning environment for DA. Here, the model generates questions from documents and conducts two explorations—one with the original document and one with a masked version. By comparing these explorations, the LLMs can independently identify and enhance its policy for reducing knowledge gaps. Experiments across various DA tasks demonstrate that autonomous learning enhances the DA performance of existing models, outperforming traditional fine-tuning and self-improvement methods. Our code is publicly available at https://github.com/FreedomIntelligence/AL.

1 Introduction

Due to the success of self-supervised and instruction tuning methods, Large language models (LLMs) could learn from unsupervised corpora (Kenton and Toutanova, 2019; Qiu et al., 2020; Han et al., 2021), supervised human-annotated instruction data (Ganin and Lempitsky, 2015; Long et al., 2016; Touvron et al., 2023b).

Recently, a series of self-improvement methods (Yuan et al., 2024; Chen et al., 2024b) are proposed to enable LLMs to be trained based on its self-generated data, Burns et al. (2023) highlights the challenges of further aligning superhuman models, as their complex behaviors are difficult for humans to effectively supervise. Since the quality of the chain of thought (CoT) can be assessed by the correctness of the final answer (Bai et al., 2022; Wang et al., 2023), a series of self-training methods (Singh et al., 2023; Hosseini et al., 2024; Yang et al., 2024) have been proposed to significantly improve LLMs' performance in math and code.

However, when we try to deploy these approaches on general DA scenarios, there are two main challenges that limit the advancement of this field. 1) **Ambiguous self-improvement reward signals**: In general DA problems, the signal used to compare the quality of two responses is implicit. 2) **Lack of high-quality instruction fine-tuning datasets**: The requirement of previous methods for high-quality data further limits the potential of model self-improvement.

It motivates us to study Autonomous Learning in a more practical DA setting, where LLMs adapt to a new domain using only a large amount of target domain unlabeled corpora. In real-world scenarios, humans demonstrate the capacity for Autonomous Learning, such as self-education through reading books or independent research of scientific papers. Most human learning processes are subjective and require minimal guidance, exhibiting strong autonomous characteristics.

To mimic human learning, it reminds us to use Autonomous Learning, an ideal approach to human education. According to (Little, 2002), it is not merely a teaching method; hence, it does not

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involve teachers dictating behaviors for students to replicate. In (Holec, 1979), the authors define Autonomous Learning as the capacity of learners to direct their own learning, implying their responsibility in shaping various aspects of the learning process. This includes critical thinking, planning, evaluating, and reflecting on learning, with learners actively monitoring the entire process (Benson, 2013). Therefore, autonomous learners are reflective individuals who consciously strive to comprehend what, why, and how they learning (Little, 1996). Consequently, while Autonomous Learning is considered an ideal approach, modern LLM training methods emphasize reliance on human-annotated data and predefined objectives when meet new downstream domain or knowledge, hindering learners' ability to monitor their learning process.

This inspirs us to adopt **AUTONOMOUS LEARNING** for LLMs. The core idea is to enable LLMs to learn autonomously, without human involvement. Autonomous Learning framework provide a self-improvement environment for DA, therefore, the only prerequisites are the LLMs itself and the learning resources, such as books or documents. The process mimics how a person learns from a book: reading to understand and closing the book to recall and identify areas that require further study to reinforce knowledge. This approach boasts several unique advantages:

1. **Self-improvement environment in DA.** Unlike passive methods, Autonomous Learning involves the model actively engaging with and understanding the material, identifying areas for improvement, and reinforcing its knowledge—emulating the human process of self-improvement through learning.

2. **No need for external annotations.** As the model undertakes its own learning journey, human intervention becomes unnecessary. The model is fed learning materials such as books, papers, or large corpora—and it dynamically improves itself without the need for annotated data from human, GPT-4 and others.

To assess the efficacy of this learning method, we have set up experiments with learning materials of varying scales, such as books (10K paragraphs), domain-specific documents (100K paragraphs), and Wikipedia (1000K paragraphs), along with corresponding public quizzes to evaluate the learning outcomes. Our experiments demonstrate that Autonomous Learning significantly outperforms pre-training and human-annotated SFT methods, suggesting that a model that has diligently 'studied' could outperform one that has 'open-book' access but no review. We also introduce recent self-improvement methods for comparison, and the experiments demonstrate the superiority of our AL's "document in the self-improvement loop." Our findings confirm that Autonomous Learning is a more effective learning method, and its independence from annotations and human involvement significantly reduces the complexity and effort involved in model training.

The main contributions of this paper are listed as follows:

- We introduce **Autonomous Learning** for LLMs' DA, a novel training paradigm that introduce a DA self-rewarding environment. This enables LLMs to perform self-improvement DA without human intervention or other stronger AI, mirroring the natural learning processes of humans.

- We demonstrate that Autonomous Learning eliminates the need for human-annotated data, allowing models to actively engage with and understand learning materials, thereby fostering self-improving learning process.

- Through rigorous experimentation using varied learning materials and corresponding public quizzes, we provide empirical evidence that Autonomous Learning outperforms traditional pre-training, SFT methods, RAG, and self-improvement method.

2 Related Work

In this section, we list some research directions related to this paper. It is important to emphasize that this paper focuses on how to leverage the powerful knowledge and instruction-following capabilities obtained through pre-training and SFT for self-learning within the document to continuously enhance domain adaptability, rather than replacing these techniques. At the end of each part, we will discuss the limitations of each section in the context of further autonomous learning.

2.1 Unsupervised Domain Adaptation

Traditional UDA methodologies encompass Pseudo-labeling (Ye et al., 2020), the Pivot-based approach (Pan et al., 2010), and adversarial neural

networks (Ganin et al., 2016). Due to success of self-supervised learning paradigm's ability to utilize large-scale unlabeled data, pre-trained language models (Kenton and Toutanova, 2019; Qiu et al., 2020; Han et al., 2021; Radford et al., 2019) based on self-supervision have become the standard paradigm in unsupervised DA.

Although protocol is concise, such methods face limitations in effectively completing downstream domain adaptation during continuous domain adaptation, because of the lack of differentiated learning strategies for various types of knowledge.

2.2 Supervised Fine-Tuning Domain Adaptation

It has been demonstrated that SFT language models on a collection of datasets expressed in instruction form (Longpre et al., 2023; Touvron et al., 2023b; Yang et al., 2023a) can improve model generalization to unseen tasks, resulting many instruction-based supervised fine-tuning methods (Chung et al., 2024; Touvron et al., 2023a,b) have been introduced. Additionally, a serious of work are proposed to adapt LLMs to structured domain (Ji et al., 2023, 2024) or specific vertical domain such as Chatlaw (Cui et al., 2023), Investlm (Yang et al., 2023b), Chatharuhi (Li et al., 2023) and HuotuoGPT series (Chen et al., 2023, 2024a).

Although exciting, the SFT method relies heavily on a large amount of high-quality annotations from humans, GPT-4 (OpenAI, 2023), or other sources, posing a formidable barrier to the scalability of instruction tuning practices for larger corpora in the future.

2.3 Self-Training and Self-Improvement

Currently, the methods for self-training and self-improvement are mainly developed in the fields of math and code. Starting with STaR (Zelikman et al., 2022), reinforced self-training (Gulcehre et al., 2023; Zhang et al., 2024), self-rewarding (Yuan et al., 2024; Chen et al., 2024b), focuses on leveraging solutions generated by the LLM to enhance its own performance. These methods involve fine-tuning the model on solutions that lead to correct answers. ReST^{EM} (Singh et al., 2023) interprets this fine-tuning as expectation-maximization based reinforcement learning for a solution-generating agent. Discovering successful solutions and how to design the critiquing signal for selecting high quality LLM responses given input queries for further model training are the most challenging problems in self-improvement methods. Early research (Bai et al., 2022; Wang et al., 2023) uses a set of manually created principles or heuristic rules to eliminate low-quality or redundant data. Additionally, Luong et al. (2024) demonstrate that RL-based fine-tuning of an LLM is difficult without initial supervised fine-tuning steps.

The success of these methods is mainly due to the clearly defined reward signals in their self-improvement loops, which makes them easier to model. In contrast, DA scenarios usually involve numerous unlabeled documents in the target domain, lacking supervisory signals. Even with extensive instruction fine-tuning datasets, the reward signals for self-improvement in general domain adaptation are implicit. Besides, this makes it difficult to apply a unified set of standards to definitively determine whether a knowledge description is `True` or `False`.

Unlike previous work, this paper introduces Autonomous Learning (AL) to address the most challenging area of implicit reward signals in the self-improvement loop for DA. **AL introduces document in the self-improvement loop.** By continuously incorporating external real documents, AL enables the model to access domain-specific knowledge and convert it into trainable data, thus avoiding reliance on self-generated data and preventing model collapse (Shumailov et al., 2024).

3 Preliminary

We define a straightforward learning objective: Given a corpus $\mathcal{D} = \{d_1, d_2, \ldots, d_n\}$ consisting of n documents, and a LLM Φ_θ with parameters θ, the goal is to enable Φ_θ to effectively learn from this corpus. The effectiveness of this learning can be evaluated using benchmarks related to $\mathcal{D}$. This process is akin to a person studying a textbook for a course and then being assessed through course exams to gauge their understanding. In our settings, AL only utilizes the source-trained model and unlabeled target data to adapt to the target domain.

4 Methodology: Autonomous Learning

In this section, we provide a detailed implementation of our proposed Autonomous Learning. The overview of our Autonomous Learning framework is shown in Figure 1. This process consists of two stages: **Stage 1. Open-book learning (Warm-up):** The model comprehends and absorbs the textual information. **Stage 2. Closed-book learning**

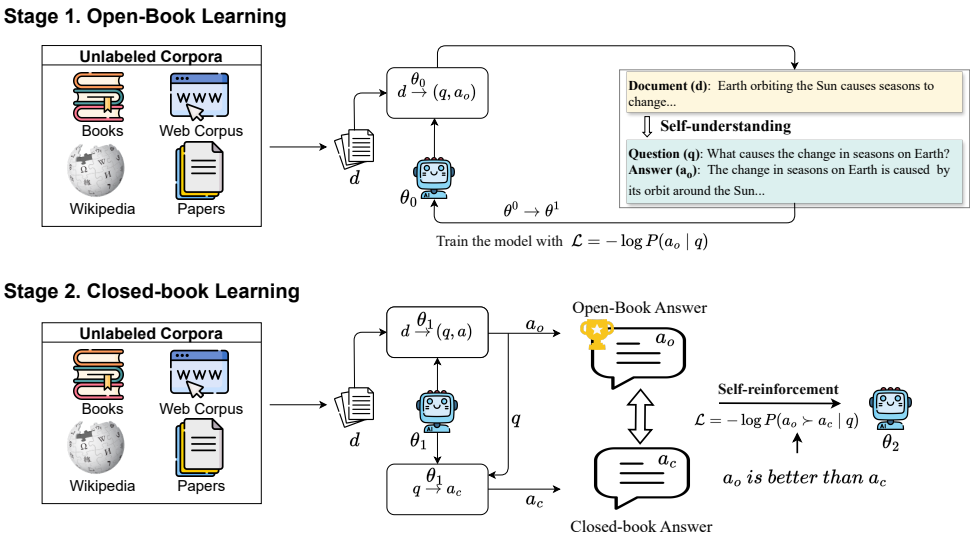

Figure 1: An ideal learning system should learn autonomously to determine *what to learn*, *how to learn* and *why to learn*. AL allows for a "document in the self-improvement loop", which allows the model to continuously learn domain corpus autonomously.

The prompt for document comprehension

```
Please create a question that closely aligns with the provided article. Ensure that the <question> does not explicitly reference the text. You may incorporate specific scenarios or contexts in the <question>, allowing the <text> to serve as a comprehensive and precise answer, at the same time, you need to generate an <answer> for the generated <question>. You can refer to the content of the article to answer, but your answer cannot reveal that you have referred to this article. Please output according to the template: '<question>: ... <answer>: ...'
<document>: [domain-specific document]
<question>:
<answer>:
```

Figure 2: The prompt for document comprehension. [domain-specific document] indicates the document d to be learned.

(Self-Improvement): The model recalls the content from the first stage, reinforcing and consolidating the learned material. The entire algorithm flow of Autonomous Learning is shown in Algorithm 1.

4.1 Stage 1. Open-Book Learning

Open-book learning simulates the process of studying a book, where we comprehend and absorb its content. The initialization model for Autonomous Learning is a LLM with comprehension abilities, denoted as Φ_{θ^0}. Given a document d to be learned, Φ_{θ^0} first comprehends d before learning it. This comprehension process can be seen as reading the document and converting it into questions and answers (QA), which can be formalized as:

$$(q, a_o) = \Phi_{\theta^0}(\text{Prompt}(d)) \tag{1}$$

Here, q and a_o represent the questions and answers generated from the document d,, and Prompt refers to the prompt used, as illustrated in Figure 2. For LLMs that cannot follow the prompts, we provide few-shot examples to enable Φ^0_θ to have comprehension abilities, as shown in . In AL, Φ^0_θ first learns from all documents $d \in D$. For documents that are too long, we split them into multiple paragraphs for learning. The objective of open-book learning is:

$$\mathcal{L}_{\text{OpenBook}}(d) = -\log P(a_o|q; \theta^1) \tag{2}$$

Thus, we obtain the model Φ^1_θ after the first stage of learning.

4.2 Stage 2. Closed-book Learning

The model Φ_{θ^1} from the first stage can be thought of as a person who has warm-up a book once. In this process, we usually close the book and recall previously learned content to enhance memory. For the LLM, the second stage involves having the model Φ_{θ^1} recall the learned content without referring to the document, thereby reinforcing the knowledge. We obtain model-generated QA pairs based on d:

$$(q, a_o) = \Phi_{\theta^1}(\text{Prompt}(d)) \tag{3}$$

Algorithm 1 The algorithm of Autonomous Learning

Input: $\Phi_{\theta^0}, \mathcal{D}$
Output: Φ_{θ^2}

// Stage 1. Open-Book Learning
$\theta^1 \leftarrow \theta^0$
for document d in $\mathcal{D}$ **do**
  $(q, a_o) \leftarrow \Phi_{\theta^0}(\text{Prompt}(d))$ // Comprehending document
  $\ell_1 \leftarrow -\log P(a_o|q;\theta^1)$
  $\theta^1 \leftarrow \text{UpdateParameters}(\ell_1, \theta^1)$ // Absorbing document
end for
// Stage 2. Close-Book Learning
$\theta^2 \leftarrow \theta^1$
for document d in $\mathcal{D}$ **do**
  $(q, a_o) \leftarrow \Phi_{\theta^1}(\text{Prompt}(d))$
  $a_c \leftarrow \Phi_{\theta^1}(q)$x
  $\ell_2 \leftarrow -\log \sigma\left(\beta \log \frac{\pi_{\theta^2}(a_o|q)}{\pi_{\theta^1}(a_o|q)} - \beta \log \frac{\pi_{\theta^2}(a_c|q)}{\pi_{\theta^1}(a_c|q)}\right)$ // Self-reinforcement
  $\theta^2 \leftarrow \text{UpdateParameters}(\ell_2, \theta^2)$
end for
return Φ_{θ^2}

Note that the questions q generated for the same d vary. For the abstracted questions q from d, Autonomous Learning has the model answer them with the book closed:

$$a_c = \Phi_{\theta^1}(q) \tag{4}$$

where a_c represents the closed-book answers. This gives us a pair (a_o, a_c). To further explore the online iterative generation of a_c, we conduct experiments in Appendix G. We aim to have the model's closed-book answers $\Phi_{\theta^1}(q)$ approximate a_o as closely as possible. To achieve this, we use a Direct Preference Optimization (DPO) strategy to help the LLM improve the review process. The advantage of DPO is its ability to quickly approximate the correct answers in the presence of biased data. The DPO learning strategy is as follows:

$$\mathcal{L}_{\text{CloseBook}}(d) = -\log \sigma\left(\beta \log \frac{\pi_{\theta^2}(a_o \mid q)}{\pi_{\theta^1}(a_o \mid q)} - \beta \log \frac{\pi_{\theta^2}(a_c \mid q)}{\pi_{\theta^1}(a_c \mid q)}\right) \tag{5}$$

where $\pi_{\theta^1}(a_c \mid q)$ represents the probability of model Φ_{θ^1} generating a_c given q. In this process, Autonomous Learning treats the open-book answer a_o as the positive answer and the closed-book answer a_c as the negative answer, achieving a self-reinforcing process. See Appendix E for a complete derivation.

5 Experiments

We evaluate our Autonomous Learning (AL) framework across various domains, including commonsense reasoning and domain-specific QA. We compare AL to traditional knowledge injection methods, assess its scalability with different dataset sizes, and its efficacy in specialized fields like medicine. We also analyze the impact of Open-Book and Closed-Book learning on performance, and evaluate AL's ability of data-efficiency under different low-resource settings.

5.1 Target Domain With Various Scales and Downstream Tasks

To highlight the superiority of our method, we consider the size of the knowledge corpus included in each dataset when selecting them, which varies from 1K to 1M. We train on knowledge corpus and test on multiple downstream tasks corresponding to these specific corpus. The details of our used benchmark is shown in Appendix B.

In all instances, we adopt a prompted zero-shot setup, wherein models are directed to address each task using natural language instructions without any accompanying contextual examples. We choose the more challenging zero-shot setup as we are interested in seeing whether Autonomous Learning works in precisely those cases where a AI system does not specify in advance which instruction should be used in which way for solving a specific problem. In fact, we let the model directly complete downstream tasks to test the model's ability to master knowledge in a specific domain. We use standard greedy decoding. The statistics of these datasets can be found in Table 1. All tasks are measured by accuracy. For tasks under Wiki, we use the reference answers after minor normalization operations mentioned in (Chen et al., 2017; Lee et al., 2019).

5.2 Experiments Setup

Experimental settings. Our research concentrates on unsupervised adaptation scenarios, utilizing Autonomous Learning on an unlabeled target domain corpus to train and enhance an initial model. We hypothesize that a robust model will demonstrate effective generalization and high performance on the target domain's test sets. Our ultimate aim is to transform this model into a domain-specific expert and an instruction model for chat applications, thereby demonstrating the potential

Dataset	Commonsense	Medical			Wiki				
	OpenBookQA	CNPLE	MedQA-en	MedQA-cn	NQ	TriviaQA	WebQA	TREC	SQuAD
Train	4957	-	10178	27400	78168	78785	3417	1353	78713
Dev	500	-	1272	3425	8757	8837	361	133	8886
Test	500	960	1273	3426	3610	11313	2032	694	10570
Number of documents for each dataset, ranging from 1K to 1M									
Documents	1326	87096	156960	163843	1M				

Table 1: The statistical information of the used benchmark.

of Autonomous Learning in model enhancement and domain-specific adaptation.

Base Model. We use the meta-llama/Llama-2-7b-chat-hf for experiments, which we call it as **initial model** in our experiments. This model originate from HuggingFace [1].

5.3 Baselines.

To compare with other baselines broadly, we replicate the setups used by prior work and reuse their reported numbers whenever possible. We note that for most tasks, our goal is not to compete with the state-of-the-art (SOTA) because: 1) for tasks like multi-choice and open domain question answering, SOTA models are trained specifically for the corresponding training sets; and 2) SOTA methods often use additional corpora for pretraining that may lead to data contamination, which could confound our domain adaptation studies. We consider the following baselines for our experiments and divide these baselines into two lines: *passive methods* and *autonomous methods*.

For passive methods, we have:

1) Pre-training: Following the traditional pre-training paradigms proposed in Kenton and Toutanova (2019); Radford et al.; Tay et al. (2022), we implement a vanilla pre-training method that adopts conventional autoregressive language modeling on given corpora.

2) Supervised Fine-tuning (SFT): We implement a SFT (Ouyang et al., 2022) method named InstructGPT to perform SFT, which utilizes a substantial amount of manually annotated data, which incurs significant costs. To avoid hallucinations, we use a stronger model to build instructions for a subset of the documents to equip the models with specific instruction following abilities, while we use the tuned model itself to build instructions for the remaining documents.

3) Retrieval Augmented Generation (RAG): RAG (Ram et al., 2023) first performs a retrieval step to identify the most relevant document fragments and then fed these documents into the LLMs to serve as the context for generating responses. We retrieve 4 documents for each question.

4) Imbalanced Learning (IL): We implement active bias (Chang et al., 2017), a widely used IL method that directly adjust the weights of examples based on the predictive distributions variance. We perform IL on pre-training and supervised fine-tuning, and get 'pre-training + IL' and 'supervised fine-tuning + IL'.

For autonomous methods, we have:

1) Self-Tuning: We implement this method (Zhang et al., 2024), in which the model completes data synthesis through self-teaching, and we also use the same amount of the data generated by the stronger model for the warm-up step of instruction following for a fair comparison.

2) SPIN: By automatically generating its own training data and learning from it, SPIN (Chen et al., 2024b) can effectively utilize human-annotated examples for supervised fine-tuning, transforming a weak language model into a powerful one. However, compared to our more rigorous experimental setting, SPIN requires initial annotated data. Therefore, to implement SPIN, we use the self-generated data used for Open-Book learning as the initial real instruction fine-tuning data of SPIN.

For all used LLMs, we use GPT-4 of version `gpt-4-0125-preview`. Meanwhile, for all methods that require warm-up datas, we construct 1,000 datas using GPT-4 for the commonsense domain and 10,000 datas for others.

5.4 Scaling Laws Across Multi-Magnitude Corpora

As training in deep learning and LLMs becomes increasingly expensive, neural scaling laws can ensure performance. Before training LLMs with hundreds of millions of parameters on massive corpora, we initially train models on smaller-scale corpora

[1] https://huggingface.co/

Model	Commonsense	Medcical			Wiki	Avg Acc.
	OBQA	MedQA-cn	MedQA-en	CNPLE	Wiki-5Datasets	
initial model	35.0	26.2	30.5	19.3	38.4	29.9
Passive methods						
Pre-training	37.0	42.6	31.4	30.4	40.2	36.3
Pre-training+IL	38.4	41.8	30.5	27.6	40.2	35.7
RAG	38.4	28.4	26.2	26.0	43.2	32.4
Supervised Fine-Tuning	42.0	52.4	33.2	41.8	42.4	42.4
Supervised Fine-Tuning+IL	41.4	53.3	33.6	42.4	42.5	42.6
Autonomous methods						
Self-Tuning	46.0	54.4	35.1	44.7	43.7	44.8
SPIN	48.4	56.1	36.3	43.1	43.3	45.4
Autonomous Learning (Ours)	**53.0**	**58.2**	**37.5**	**46.4**	**44.6**	**47.9**

Table 2: Results on Common sense, Medical corpora and Wiki corpora. The number of documents has increased from 1,000 to 1,000,000, representing a three-order-of-magnitude growth from the commonsense domain to the Wiki domain. The best performances are highlighted in **bold**, while sub-optimal ones are marked with underline.

and fit scaling laws for training on larger corpora.

Unlike previous work (Henighan et al., 2020; Yang et al., 2023a), which typically fix the size of the corpus and vary the scale of model parameters to observe the effects on error, this paper's scaling laws focus more on the corpus. The aim is to demonstrate through experiments on scaling laws of corpora size that our method is universally effective across various scales of corpora. As shown in Table 2, the benchmark results demonstrate that the Autonomous Learning outperforms all the currently most popular knowledge learning paradigms across various document scales. In specific domains such as Medical, the method described in this paper still shows significant improvements.

Model/Method	MedQA-en	OBQA	CNPLE
Llama-3.1-8B-Instruct			
- initial model	0.386	0.786	0.310
- SFT	0.405	0.804	0.442
- SPIN	0.416	0.817	0.456
- Ours	**0.431**	**0.829**	**0.481**
Qwen2.5-7B-Instruct			
- initial model	0.335	0.368	0.560
- SFT	0.366	0.431	0.614
- SPIN	0.375	0.503	0.631
- Ours	**0.391**	**0.548**	**0.678**

Table 3: Experiment of deploying AL on various LLMs as our initial models.

5.5 Effects on Various Models

To highlight the scalability of our method, we deploy our experiments using modern powerful models like Llama-3.1-8B-Instruct and Qwen2.5-7B-Instruct in Table 3 Compared to the initial models and other enhancement methods such as SFT and SPIN, our approach consistently achieved the best scores on all testset, demonstrating its ability to enhance model generalization and performance. The consistent performance improvements observed across different models, indicating the strong generalizability of our AL.

5.6 Ablation Study

To better explore the impact of each part of our model, we conducted ablation studies and the results are shown in Table 4. By analyzing the comprehensive ablation experiment settings, we can draw the following conclusions: 1) All ablation models can improve the capabilities of the initial model. 2) Closed-book learning is better than open-book only (ablation model I).

Furthermore, we find that **ablation model IV yield results as expected, even lower than the initial model.** One possible explanation is that when removing all terms related to the closed-book answer a_c from the learning objective Formula 5 during the closed-book learning phase, the learning objective of closed-book learning approximates open-book learning. Consequently, training for more epochs leads to overfitting, thereby reducing effectiveness. This finding highlights the effectiveness of AL, wherein self-reflective knowledge contrast further strengthens the model's ability to generalize knowledge. The more detailed experimental results regarding the generalization performance of the Autonomous Learning in two stages are presented in Appendix D. The experimental results indicate that, without the need for additional external annotations, Closed-Book learning can further enhance the domain adaptation performance of existing fine-tuning paradigms.

	Ablation model	OBQA	MedQA-cn	MedQA-en	CNPLE
-	initial model	35.0	26.2	30.5	19.3
I	open-book only	40.0	51.4	32.4	40.5
II	closed-book only	44.4	52.6	33.7	42.3
III	closed-book → open-book	48.4	54.3	35.2	44.1
IV	AL w/o a_c in closed-book	33.6	25.4	28.3	19.6
VI	open-book → closed-book (AL)	**53.0**	**58.2**	**37.5**	**46.4**

Table 4: Ablation study. Ablation model III represents training first with the closed-book method, followed by the open-book method.

	OBQA	MedQA-cn	MedQA-en	CNPLE
initial model	35.0	26.4	30.5	19.3
SFT	42.0	50.3	33.0	40.8
AL				
- full Doc.	**53.0**	**58.2**	**37.5**	**46.4**
- fewer Doc.				
# 30%	50.2	56.9	36.6	45.6
# 15%	44.2	52.4	35.3	43.3
# 5%	38.6	51.6	34.2	39.5

Table 5: Low-resource settings where it adopts fewer documents in Autonomous Learning (AL).

Interestingly, when we directly perform closed-book learning (the ablation model III), the performance has certain advantages compared to open-book learning, but this effect is still far lower than the complete Autonomous Learning model. The reason may be due to the lack of learning of all documents by the model in the open-book learning stage. As a result, when closed-book learning is performed directly, although the model's learning method based on self-knowledge comparison can learn a certain amount of knowledge, it is still under-fitting.

To demonstrate that AL is not dependent on warm-up data, we use few-shot prompting to enable the llama-2 model to generate D->QA instruction fine-tuning data independently. We then conducted experiments based on the model's self-synthesized warm-up data. Table 6 show that AL can consistently output all baseline models.

Model/Method	**MedQA-en**	**OBQA**	**CNPLE**
Llama-2-7b-chat			
- initial model	30.5	0.350	19.3
- SFT	31.4.	0.420	41.8
- SPIN	36.3	0.484	43.1
- AL	**37.5**	**0.530**	**46.4**
- AL w/o warm-up	36.7	0.514	44.7

Table 6: Performance without warm-up dataset. We still provide the necessary warm-up data to baselines.

5.7 Competitive Performance Achieved by Fewer Documents

The Closed-Book phase of our approach aims to enhance the model's generalization of learned knowledge and can be seamlessly integrated into any model that has undergone the Open-Book learning phase to further enhance its learning effectiveness. To investigate the knowledge enhancement effects of our approach in the Closed-Book learning phase, we conducted an in-depth exploration of the relationship between model performance and the quantity of documents used for reinforced knowledge learning in this phase.

Table 5 illustrates the experimental results of our approach in the Closed-Book phase under different scales of document subsets. It can be observed that our approach in the Closed-Book phase demonstrates performance comparable to the full dataset when based on only 30% of the documents. Additionally, when only 5% of the documents are available, our approach rapidly enhances the model's generalization of knowledge, achieving performance on par with SFT.

This highlights the efficient utilization of documents by our approach, which can extract rich knowledge through self-learning even with a small number of documents, thereby enhancing the model's generalization of knowledge.

6 Conclusion

In this paper, we explore the significant challenges associated with enabling LLMs to autonomously adapt to new domains by leveraging extensive unlabeled target corpora. We propose and validate **Autonomous Learning**, which innovatively introduces a self-improvement environment for DA. By enabling LLMs to self-educate through direct interaction with diverse textual materials, this approach not only mimics human learning processes but also significantly enhances the capabilities of LLMs be-

yond the constraints of traditional training methods reliant on human-annotated data. With the help of sufficient pre-training and SFT, our results show that AL outperforms all baselines without any additional human annotations.

Limitations

Despite its promising performance in three domain adaptation tasks, AL has several limitations that must be considered:

- **Limited Autonomous Learning Data Format:** AL focuses on the most practically significant domain adaptation setting, where the target domain has a large amount of unlabeled data. It explores how to use these datas for domain adaptation through a self-improvement paradigm. However, current AL methods only focus on text modality and its unlabeled corpora. In future work, AL should support more diverse multimodal domain adaptation scenarios.

- **Additional Computational Cost:** Although AL can further push the boundaries of domain adaptation beyond existing methods, it requires two inferences per step in closed-book learning, which increases the overall training time. This suffers from the same shortcomings as recent self-training-based methods, such as ReST (Gulcehre et al., 2023),self-rewarding (Yuan et al., 2024), self-play (Chen et al., 2024b). In future research, simpler AL methods need to be explored to improve the training efficiency of the AL framework.

- **Limited to Models with Instruction-Following Capabilities:** The method of this paper starts directly from an initial model, which needs to have sufficient instruction-following capabilities to complete both open-book and closed-book answers. However, for models that do not possess this instruction-following capability like GPT-2 (Radford et al., 2019), we can use chat models like Llama-2-7b-chat-hf (Touvron et al., 2023b), Baichuan 2-Chat-7b (Yang et al., 2023a), ChatGPT (OpenAI, 2022) to simply construct instruction fine-tuning datasets to enable them to master the instruction-following required for Autonomous Learning.

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A Ethics Statement

The datasets used in this study are all derived from publicly available resources on the internet and are freely accessible. And the backbone models we use are also publicly available. Therefore, there is no need for ethics concern.

B Target Domain With Various Scales and Downstream Tasks

Below we describe each domains and its corresponding downstream tasks.

Commonsense: We choose a small-scale corpus dataset in the domain of common sense, OpenBookQA, which contains a corpus of 1,326 common sense entries to serve as reference knowledge for test data.

- **OpenBookQA (OBQA)** (Mihaylov et al., 2018) comprises 5,957 multiple-choice questions, each offering four possible answers. The dataset is combined with external fundamental scientific facts. To successfully answer these questions, one must have a comprehensive understanding of these fundamental scientific facts. and its applications.

Medical: We pick three widely used datasets in Medical domain. Each dataset is accompanied by a medical textbook, which contains the knowledge required to answer the questions in the dataset. We split the textbook corpus into multiple documents, each containing no more than 512 tokens. After dividing the textbooks, the CNPLE, MedQA-en, and MedQA-cn datasets contain 87,096, 156,960, and 163,843 documents, respectively. Please note that MedQA-cn and CNPLE are written in Chinese.

- **MedQA-en** (Jin et al., 2021) gathers questions from the National Medical Board Examinations of the USA. MedQA presents a demanding benchmark because it incorporates diverse medical knowledge—including patient profiles, disease symptoms, and drug dosage requirements. This variety requires contextual understanding for accurately answering the questions posed.

- **MedQA-cn** (Jin et al., 2021) is also collected from the National Medical Board Examinations of the Mainland China. For both MedQA-en and MedQA-cn, we test them on the 4-option questions.

- **The 2023 Chinese National Pharmacist Licensure Examination (CNPLE)** (Chen et al., 2023) is a fresh medical exams. Addressing data contamination in the training of Large Language Models (LLMs) is challenging, particularly when dealing with complex and vast datasets (Huang et al., 2023). To mitigate this issue, we use the 2023 Chinese National Pharmacist Licensure Examination, conducted on October 21, 2023, as our benchmark. The release date of this dataset is later than all the base and chat models we used, therefore it can prevent data leakage and ensure reliable evaluations.

Wiki: We use the same five QA datasets and training/dev/testing splitting method as in previous work (Lee et al., 2019). For datasets under this part, we train on the documents in Wiki corpus as their common corpus. Here, we select a subset of the Wikipedia corpus that contains 1 million documents.

- **Natural Questions (NQ)** (Kwiatkowski et al., 2019) was designed for end-to-end question answering. The questions were mined from real Google search queries and the answers were spans in Wikipedia articles identified by annotators.

- **TriviaQA** (Joshi et al., 2017) contains a set of trivia questions with answers that were originally scraped from the Web.

- **WebQuestions (WQ)** (Berant et al., 2013) consists of questions selected using Google Suggest API, where the answers are entities in Freebase.

- **CuratedTREC (TREC)** (Baudiš and Šedivỳ, 2015) sources questions from TREC QA tracks as well as various Web sources and is intended for open-domain QA from unstructured corpora.

- **SQuAD v1.1** (Rajpurkar et al., 2016) is a popular benchmark dataset for reading comprehension. Annotators were presented with a Wikipedia paragraph, and asked to write questions that could be answered from the given text.

We collectively refer to these datasets as Wiki-5Datasets in out experiments.

	Hyperparameters	OpenBookQA	CNPLE	MedQA-en	MedQA-en	wiki
Open-Book Stage	Optimizer	AdamW				
	Warmup Ratio	0.1				
	Learning Rate	2e-5				
	LR Schedule	cosine				
	Batch Size	8				
	Max Length	2048				
	# Epoch	3				
Closed-Book Stage	Optimizer	Rmsprop				
	Warmup Ratio	0.2				
	Learning Rate	5e-7				
	LR Schedule	Linear				
	Batch Size	8				
	Max Length	2048				
	DPO beta	0.01				
	# Epoch	3				

Table 7: The hyperparameters used for Our Autonomous Learning on all benchmark.

C Hyperparameters of Autonomous Learning

The training hyperparameters of Autonomous Learning on different datasets are reported in Table 7. For all of the hyperparameters, we directly use the same value across all datasets. The training was conducted on a GPU server with 8 NVIDIA A100 GPU cards.

D Naive Empirical Risk Minimization is Not Enough

In this section, we emphasize the point of this paper, that Naive Naive Empirical Risk Minimization (EMR) is not enough, through trend charts on various datasets. In Figures 3, it can be observed that all Naive EMR methods exhibit clear plateaus, and additional epoch training does not yield higher performance but rather leads to overfitting. The closed-book learning method introduced in the second stage of this paper further enhances the model's domain adaptation, resulting in improved accuracy for the corresponding tasks, indicating the effectiveness of the knowledge-contrasting approach proposed in this paper.

E Mathematical Derivations of AL

In this appendix, we will clarify that our approach is a process of autonomously enhancing domain adaptation based on knowledge comparison, rather than simply praising or criticizing. We propose the advantages of RL methods in two ways.

First, by (Rafailov et al., 2023) Section 4, the gradient of DPO loss is:

$$\nabla_\theta \mathcal{L}_{DPO} = -\beta E_{(x,y_w,y_l)\sim D}[\sigma(\hat{r}_\theta(x,y_l) - \hat{r}_\theta(x,y_w))(\nabla_\theta \log \pi_\theta(y_w|x) - \nabla_\theta \log \pi_\theta(y_l|x))] \quad (6)$$

where (x, y_w) and (x, y_l) are the chosen and rejected responses, respectively. The updated parameters of the model will move in the direction making the difference $\nabla_\theta \log \pi_\theta(y_w|x) - \nabla_\theta \log \pi_\theta(y_l|x)$ become larger with a weight function $\sigma(\hat{r}_\theta(x, y_l) - \hat{r}_\theta(x, y_w))$, not just increase the log probability of the chosen one and decrease the log probability of the rejected one. Actually in (Rafailov et al., 2023), it has been shown that if we just increase the chosen probability and decrease the rejected probability, the language model will degenerate. Our experiment (Figure 5) shows that the rewards of chosen and rejected responses can be increase or decrease simultaneously.

Second, by Equation (4) in (Rafailov et al., 2023), the optimal solution of the KL-constrained reward maximization objective is:

$$\pi(y|x) = \frac{1}{Z(x)} \pi_{ref}(y|x) \exp(\frac{1}{\beta} r(x,y)) \quad (7)$$

for the given reference model π_{ref} and reward r, where $Z(x)$ is the normalization factor independent of the responses. Hence we can see that the optimal solution is not just choose the best response and ignore all other ones, it is distributed to all responses with the probability determined by the reward function and β, higher reward leads to higher probability. It can be seen that for two different responses y_1, y_2, although there is a better one, but if they are both good enough, that means $r(x, y_1)$ and $r(x, y_2)$

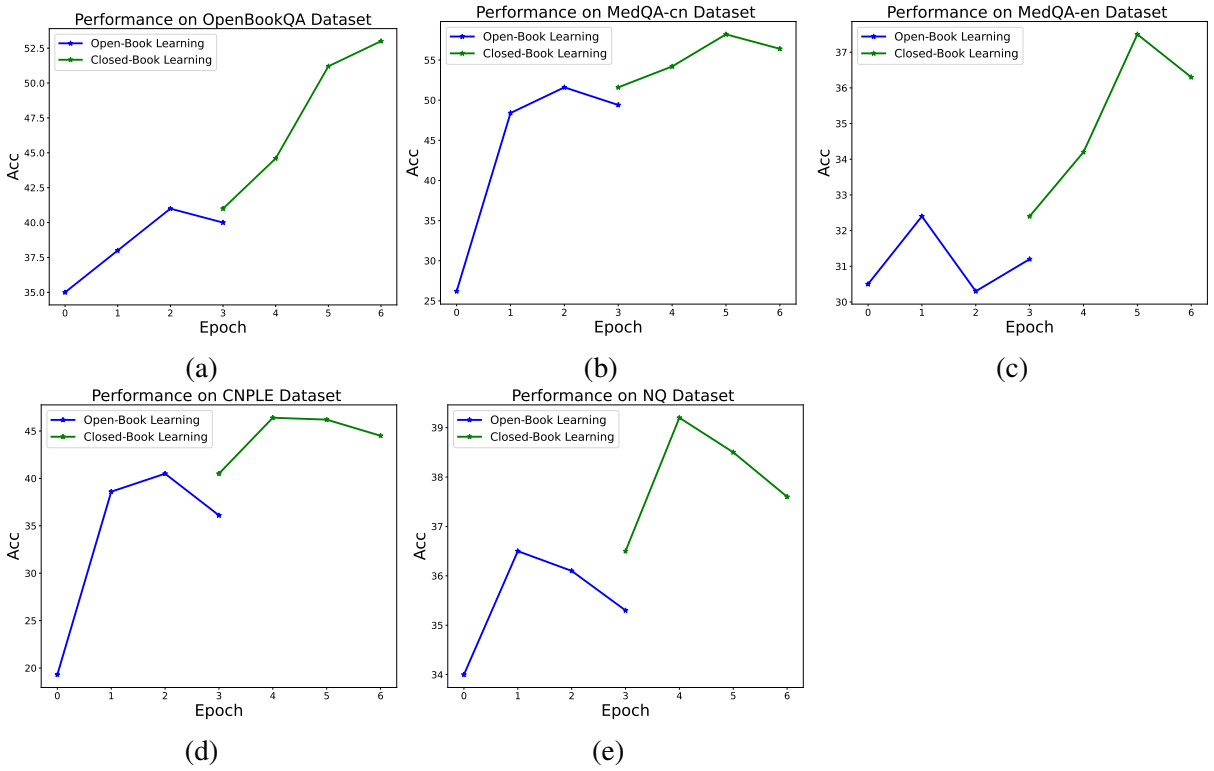


Figure 3: The performance gap between open-book learning and closed-book learning. Epoch 0 stands for the performance of initial model. Epochs 4 to 6 represent the 1st, 2nd, and 3rd epochs of closed-book learning, respectively.

are closed with each other, there probabilities in the optimal distribution will be closed. So the RL methods for the LLM training is not just praising or criticizing, but only depends on their actually rewards. Responses with high reward values will have high probabilities in the end.

F Demonstrating How Autonomous Learning Works Through Examples

In this appendix, we demonstrate how Autonomous Learning works through some examples. As shown in Figure 6, we observe that after one epoch of closed-book learning, the closed-Book answer in Epoch 2 aligns better with the learned documents and questions that the closed-book answer in Epoch 1.

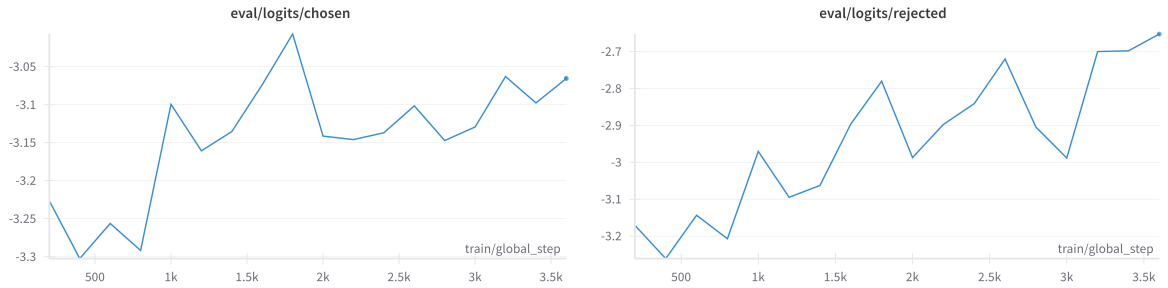
G Impact of Online Iterative Data Generation

To explore the online iterative generation of a_c, we designed an experiment where, after training the model with k samples, we regenerate a_c and a_o for subsequent training based on the updated model. We tested various values of k in (4096, 16,384, 65,536, and 131,072) to observe the performance trends. The experiment was conducted using the llama-2-7b-chat-hf model.

We observe that when the update frequency is high (i.e. when k is 4096), the model's performance actually deteriorates. Conversely, the model performs best when k is set to 65,536. However, increasing k to 131,072 does not lead to further improvements. The possible reason for this is that a high update frequency implies the model uses relatively less data for training in each iteration, which may cause it to over-fit the most recently observed data, thus affecting its generalization ability and leading to unstable learning. As we gradually re-

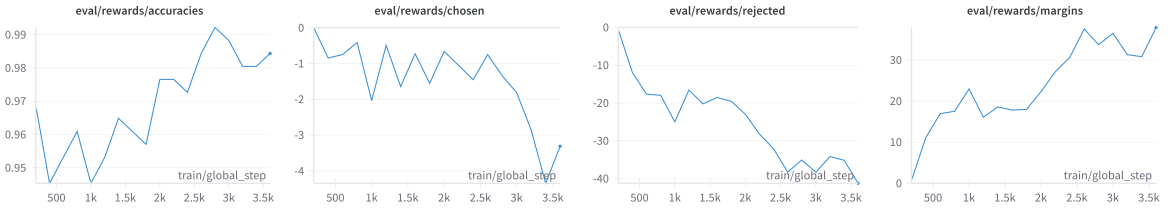
Model/Method	**MedQA_en**	**CNPLE**
initial model	0.305	0.193
offline AL (Ours)	0.375	0.464
online AL		
- k=4096	0.352	0.446
- k=16384	0.369	0.463
- k=65536	0.383	0.479
- k=131072	0.364	0.456

Table 8: The impact of online iterative data generation



(a) Logits for the open-book answer. (b) Logits for the closed-book answer.

Figure 4: The trend of logits variation for open-book answers and closed-book answers on the MedQA-cn dataset.



(a) Reward accuracy (b) Reward chosen (c) Reward rejected (d) Reward margins

Figure 5: Reward performance on MedQA-cn dataset.

duce the update frequency, we find a performance inflection point that surpasses offline AL. This observation suggests that finding the optimal balance between data efficiency and learning stability is crucial. Future research should focus on designing a more effective online AL strategy to achieve this balance.

<|system|>
You are KnowledgeGPT, equipped with in-depth knowledge. Your task is to directly answer the user's question.
<|user|>
[question] What is an example of a film that combines comedy with a critique of human vices through interwoven stories, highlighting the impact of greed among others?
<|assistant|>
[answer] An example of a film that skillfully combines comedy with a critique of human vices, specifically focusing on the theme of greed among others...

Table 9: An example of our $\mathcal{QA}$ instruction tuning data.

Epoch 1

{Reference document}
An example of hunting is an otter cracking open clams with a rock
{Question}
What is an example of how otters use tools in their dietary habits?
{Open-book answer}
An example of how otters use tools in their dietary habits is by using rocks to crack open clams. This behavior demonstrates their ability to adapt and manipulate their environment to access food, showcasing their intelligence and problem-solving skills.
{Closed-book answer}
Otters are known to use tools in their dietary habits by using rocks to crack open clams and other shellfish. They have been observed holding the shells in their paws and then slamming them on rocks to break them open. This behavior demonstrates their problem-solving skills and adaptability in their dietary habits.

Epoch 2

{Reference document}
An example of hunting is an otter cracking open clams with a rock
{Question}
What is an example of a hunting technique utilized by otters?
{Open-book answer}
An example of a hunting technique utilized by otters is using rocks to crack open clams.
{Closed-book answer}
An example of a hunting technique employed by otters is using rocks to trap prey. They will often place a fish on a rock, which then serves as a makeshift platform for the otter to drain the water from the fish before consuming it. This strategy is a clever and efficient method of hunting in their aquatic environment.

Figure 6: An example to show how Autonomous Learning works.

Please create a question that closely aligns with the provided article. Ensure that the <question>does not explicitly reference the text. You may incorporate specific scenarios or contexts in the <question>, allowing the <text>to serve as a comprehensive and precise answer, at the same time, you need to generate an <answer>for the generated <question>. You can refer to the content of the article to answer, but your answer cannot reveal that you have referred to this article. Please output according to the template '
<question>:...
<answer>:....'
<document>: [domain-specific document]
<question>:
<answer>:

Figure 7: The prompt for question generation. [domain-specific document] refers to a document in the domain-specific pre-training corpora.

You are KnowledgeGPT, equipped with in-depth knowledge. Your task is to directly answer the user's question.
<question>: [question generated by LLM]
<answer>:

Figure 8: The prompt for the answer generation of $\mathcal{QA}$. [question generated by LLM]] is the previously text-derived query in Figure 7.