SELF-QUESTIONING LANGUAGE MODELS

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ABSTRACT

Can large language models improve without external data – by generating their own questions and answers? We hypothesize that a pre-trained language model can improve its reasoning skills *given only a single prompt* specifying the topic (e.g., algebra word problems) and asking the model to generate its own questions. To do this, we propose Self-Questioning Language Models (SQLM): an asymmetric self-play framework where a proposer is given the topic and generates a question for a solver, who tries to answer it. Both the proposer and solver are trained via reinforcement learning. The proposer receives a reward if the problem is not too easy or too difficult, and the solver receives a reward based on majority voting, a proxy for correctness in the absence of ground-truth answers. For coding, the proposer can instead generate unit tests which are used for verification. We study this asymmetric self-play framework on three benchmarks: three-digit multiplication, algebra problems from the OMEGA benchmark, and programming problems from Codeforces. By continually generating more interesting problems and attempting to solve them, language models can improve on downstream benchmarks without access to any curated training datasets. Website: `self-questioning.github.io`.

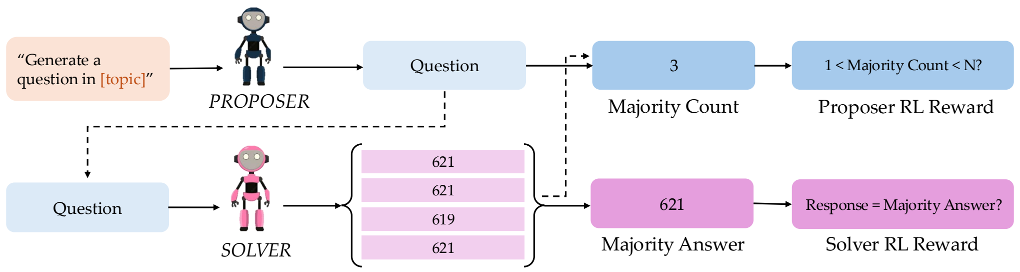


Figure 1: Overview of Self-Questioning Language Models. The only input to the system is a single prompt, given to the proposer. The proposer generates a question related to the given topic, and the solver aims to solve the question. The solver's reward is computed by using the majority vote as a proxy for the ground-truth answer. The proposer's reward is computed based on how many of the answers match the majority answer, to encourage problems not to be too easy or too difficult.

1 INTRODUCTION

The post-training of large language models still relies heavily on hand-curated datasets (Yu et al., 2025a; Li et al., 2024), demanding substantial engineering effort and human supervision. In an attempt to alleviate this burden, researchers have developed unsupervised reward functions for reinforcement learning, which use proxies such as the model's internal confidence (Zhao et al., 2025; Prabhudesai et al., 2025) or the majority answer (Zuo et al., 2025) in the absence of ground-truth rewards or answers. However, these methods still presuppose the existence of well-formed input prompts or questions, and the bottleneck shifts from curating labeled answers to curating high-quality questions – a task that remains labor-intensive and not easily automated at scale. This highlights a critical gap in current methodologies: the lack of scalable, self-sustaining pipelines for generating meaningful questions and answers without human intervention.

Interestingly, pre-trained language models themselves represent a largely untapped resource for addressing this challenge. Much like humans, these models can be seen not only as passive recipients of training data but also as active generators of it. As an extreme analogy, human beings confined to limited environments such as jail cells could engage in self-reflective and cognitively enriching exercises by generating and answering their own questions. Large language models pre-trained on trillions of tokens of text may possess similar capabilities. By leveraging their intrinsic knowledge and reasoning faculties to simulate both the role of question-asker and responder, models could drive their own intellectual development in a closed-loop fashion. This paradigm opens a compelling avenue for self-supervised post-training that could reduce dependence on curated datasets and unlock a new frontier in autonomous language model refinement.

To explore this paradigm, we propose **S**elf-**Q**uestioning **L**anguage **M**odels (SQLM): an asymmetric self-play framework in which a pre-trained language model is prompted with a high-level domain (e.g., "algebra word problems") and learns to improve by generating and solving its own problems. Asymmetric self-play was first proposed by OpenAI et al. (2021) and applied to goal-conditioned robotic manipulation; here, we apply it to language model post-training, where the model plays two roles: a proposer that creates new problems and a solver that attempts to solve them. Both roles are trained via reinforcement learning. When the generator-verifier gap is small (such as in arithmetic, where solution generation and verification are similarly difficult), we use majority voting over multiple solver outputs as a proxy for correctness. When the gap is large (such as in code generation, where verifying via unit tests is easier than writing a correct solution), we instead rely on external verification signals like test results. The proposer is rewarded for generating non-trivial, solvable problems, while the solver is rewarded for correctness under these domain-specific criteria.

We evaluate this framework three benchmarks: three-digit multiplication, algebra problems from the OMEGA (Sun et al., 2025) benchmark, and coding problems from Codeforces. In every case, training begins with a single prompt describing the task, without any example problems or labeled data. As training progresses, both the proposer and solver improve iteratively, guided by reinforcement signals based solely on internal agreement or external verification. Evaluation on human-curated benchmarks shows that models trained in this self-supervised manner can significantly outperform their initial versions, demonstrating meaningful gains in reasoning ability without access to any curated training datasets. These results point to the promise of self-play as a general mechanism for self-improvement in language models.

2 Related Work

2.1 Reinforcement Learning for Language Models

Reinforcement learning (RL) has played a pivotal role in the alignment and reasoning capabilities of contemporary large language models. Early efforts primarily focused on aligning model outputs with human preferences via Reinforcement Learning from Human Feedback (RLHF), using algorithms such as Proximal Policy Optimization (PPO) (Schulman et al., 2017) and Direct Preference Optimization (DPO) (Rafailov et al., 2023). In structured domains such as mathematics and code generation, RL has expanded beyond preference modeling to leverage the availability of ground-truth solutions. This enables the use of binary reward signals, allowing for more objective fine-tuning. Approaches like STaR (Zelikman et al., 2022) and $ReST^{EM}$ (Singh et al., 2023) exploit this structure by sampling rationales from the model and selectively fine-tuning on those that yield correct final answers. This selection-based training paradigm encourages more reliable intermediate reasoning steps. A parallel line of work has explored self-refinement capabilities in LLMs, training models to identify and correct their own mistakes through recursive or feedback-driven mechanisms (Kumar et al., 2024; Qu et al., 2024). These methods aim to internalize self-correction as a policy, rather than relying solely on external signals. On the algorithmic front, recent work has introduced RL algorithms specifically tailored for chain-of-thought (CoT) (Wei et al., 2022) reasoning. GRPO (Shao et al., 2024), Dr. GRPO (Liu et al., 2025c), and DAPO (Yu et al., 2025a) have been instrumental in achieving state-of-the-art performance on complex reasoning benchmarks. Most notably, models such as DeepSeek-R1 (Guo et al., 2025; Hu et al., 2025) have demonstrated that targeted RL techniques can substantially enhance general reasoning capabilities.

2.2 Unsupervised Rewards for Reasoning

Ground-truth answers and external verifiers are often costly or impractical to obtain. This has motivated recent work exploring how far one can go without any form of external supervision. Notably, several studies have demonstrated that pre-trained language models are sufficiently well-calibrated to use their own confidence as a training signal. This has been operationalized through entropy minimization (i.e., reverse KL divergence to a uniform distribution) (Prabhudesai et al., 2025), and forward KL divergence (Zhao et al., 2025). Another unsupervised reward strategy treats the majority prediction among sampled completions as the ”correct” answer (Zuo et al., 2025). These approaches rely solely on the model’s internal uncertainty and consensus, eliminating the need for labeled data or external evaluators. Building on this line of work, our approach goes a step further: not only does it not require ground-truth answers, it does not even require human-authored questions. Instead, the model itself is used to generate questions, making the entire pipeline fully self-supervised.

2.3 Synthetic Data Generation

As models grow larger and more data-hungry, generating high-quality training data has become increasingly important. Synthetic data generation (Nadas et al., 2025; Wang et al., 2024; Long et al., 2024) has emerged as a powerful strategy for scaling up LLM training. A strong ”teacher” model is used to produce high-quality examples, which are then used to train a target model. Notably, synthetic data has played a central role in the development of large-scale models such as K2 (Liu et al., 2025b). In these cases, synthetic data is generated prior to training and treated as a static dataset and the generation process is usually guided by heuristics or templates.

2.4 Exploration

Exploration is a foundational challenge in reinforcement learning. To address this, many methods encourage agents to discover novel states through intrinsic rewards. One prominent class is based on prediction error, where novelty is measured by the agent’s surprise at its own predictions, such as inverse dynamics models (ICM) (Pathak et al., 2017) or randomly initialized networks (RND) (Burda et al., 2018). Other techniques optimize state entropy to promote diverse state visitation (Liu & Abbeel, 2021). Go-Explore (Ecoffet et al., 2019) separates exploration and robustification, enabling agents to return to promising states and expand from there, while Plan2Explore (Sekar et al., 2020) uses a world model to target states with high epistemic uncertainty. Asymmetric self-play (OpenAI et al., 2021) frames exploration as a game between agents, fostering curriculum learning. More recently, exploration concepts have been applied to LLMs for personalization (Wan et al., 2025) and safety alignment (Liu et al., 2025a). Furthermore, recent work (Zweiger et al., 2025) introduces a reinforcement learning loop where models generate their own finetuning data and weight update directives, enabling persistent self-directed adaptation to new tasks and knowledge.

3 Preliminaries

3.1 Reinforcement Learning for Language Models

The language modeling task of generating answers for a given question can be treated as a one-step reinforcement learning problem. For a question x sampled from the dataset $\mathcal{D} = \{(x, y)\}$, the policy $\pi(y_{\text{pred}}|x)$ generates a response y_{pred}, for which it receives some reward $r = \mathcal{R}(x, y_{\text{pred}}, y)$. The reward is traditionally computed via a measure of similarity of y_{pred} and y, e.g., using hard-coded parsers, model-based verifiers (Ma et al., 2025), or probability-based rewards (Zhou et al., 2025; Yu et al., 2025b). In these settings, RL is used to train the policy to maximize the expected reward

$$\mathbb{E}[r] = \mathbb{E}_{y_{\text{pred}} \sim \pi(y_{\text{pred}}|x)}[\mathcal{R}(x, y_{\text{pred}}, y)].$$

Recently, several unsupervised reward functions $\mathcal{R}(x, y_{\text{pred}})$ have been proposed. These rewards do not rely on having access to the ground truth y, instead using majority voting (Zuo et al., 2025), entropy (reverse KL divergence) (Prabhudesai et al., 2025), forward KL divergence (Zhao et al., 2025), or even random rewards (Shao et al., 2025).

3.2 Asymmetric Self-Play

Asymmetric self-play (OpenAI et al., 2021), first proposed for goal-conditioned robotic manipulation, is a method for self-supervised exploration which naturally produces a curriculum of interesting tasks for agents to use for learning. It trains two RL agents: a proposer P who aims to propose challenging tasks, and a solver S who aims to solve those tasks. The proposer receives a reward if the solver fails to solve the task, and the solver receives a reward for solving its assigned task. We refer the reader to OpenAI et al. (2021) for more details on the original application of asymmetric self-play to robotics.

In our language modeling setting, we consider a proposer policy $\pi_{P_t}(x)$ and solver policy $\pi_S(y_{\text{pred}} \mid x)$, where P_t is simply a proposer constrained to a specific topic t (e.g., arithmetic), x is a generated question, and y_{pred} is an attempt at solving the question. Here, both P and S are language models and trained via reinforcement learning as described in the next section.

4 Method

4.1 Minimax Objective

The proposer policy $\pi_{P_t}(x)$ and the solver policy $\pi_S(y_{\text{pred}} \mid x)$ are both trained via reinforcement learning to maximize their expected rewards:

$$\begin{aligned} \text{Solver:} \quad & \mathbb{E}_{x \sim \pi_{P_t},\, y_{\text{pred}} \sim \pi_S(\cdot \mid x)} \left[\mathcal{R}_S(x, y_{\text{pred}}) \right], \\ \text{Proposer:} \quad & \mathbb{E}_{x \sim \pi_{P_t},\, y_{\text{pred}} \sim \pi_S(\cdot \mid x)} \left[\mathcal{R}_P(x, y_{\text{pred}}) \right], \end{aligned}$$

This setup involves self-play as the proposer's output is used to condition the solver, and the solver's output is used to compute a reward, which is then used to train the proposer. Figure 1 shows an overview of our method. In the next subsection, we discuss how to design reward functions for the proposer and solver, given that this setting is fully self-supervised in the absence of ground-truth answers and perfect verifiers.

4.2 Reward Functions

In the context of self-play without access to ground-truth answers, a central challenge is how to perform verification. One straightforward approach is to have the proposer not only generate a problem but also provide a corresponding solution. The solver's output can then be compared against the proposer's solution to assess correctness. However, there is no inherent reason to trust the proposer's solution over the solver's. In most self-play setups, both models are initialized from the same pre-trained language model (and in our experiments, also share weights). As a result, both are equally susceptible to error, making verification by mutual agreement unreliable.

This issue relates closely to the concept of the generator-verifier gap (Song et al., 2024), which refers to the difference in difficulty between generating a correct solution and verifying the correctness of a given solution. In arithmetic, computing the sum of two numbers and verifying that sum are nearly equivalent in difficulty. However, writing a correct implementation for a programming problem may be difficult, whereas verifying its behavior (e.g., through unit tests) is often easier. Depending on the type of problem, we propose different approaches to designing the proposer and solver.

When the generator-verifier gap is small. In domains such as arithmetic, there is no easy way to verify solutions without performing reasoning that is similarly complex to what is required to generate the solution itself. For these cases, we do not ask the proposer to generate a solution, and instead use majority voting (Zuo et al., 2025) as a self-supervised reward for the solver. Specifically, for each problem, we sample N generations from the model and use the majority answer as a proxy for the correct answer. All generations that match the majority answer are given a reward of 1 and all other generations are given a reward of 0.

Let $x \sim \pi_{P_t}$ be a problem sampled from the proposer, and $y_1, \ldots, y_N \sim \pi_S(\cdot \mid x)$ be N independent solver generations. Let y_{maj} be the majority answer among the N generations. The solver reward is:

$$\mathcal{R}_S(x, y_i) = \begin{cases} 1 & \text{if } y_i = y_{\text{maj}}, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

The proposer reward is based on how "reasonable" the problem is: it receives a reward of 0 if all N generations match (too easy) or if none match (too hard), and a reward of 1 otherwise:

$$\mathcal{R}_P(x) = \begin{cases} 1 & \text{if } 0 < |\{y_i : y_i = y_{\text{maj}}\}| < N, \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

When the generator-verifier gap is large. In domains such as coding where verification is easier than generation, we can do better by leveraging the proposer's ability to generate a solution or information useful for verification such as test cases. In this section, we focus on the use-case of coding for concreteness, but one could design variants of this approach for other domains.

Let $x \sim \pi_{P_t}$ be a problem and associated test cases generated by the proposer. Let $y_{\text{pred}} \sim \pi_S(\cdot \mid x)$ be the solver's solution, and let $\text{Tests}(x)$ denote the set of unit tests provided with x. Define $\text{Pass}(y_{\text{pred}}, \text{Tests}(x)) \in [0, 1]$ as the fraction of unit tests passed by the solver's output. Then:

$$\mathcal{R}_S(x, y_{\text{pred}}) = \text{Pass}(y_{\text{pred}}, \text{Tests}(x)) \tag{3}$$

The proposer is again rewarded for generating problems that are non-trivial but solvable. It receives a reward of 1 if the solver passes some, but not all, test cases:

$$\mathcal{R}_P(x, y_{\text{pred}}) = \begin{cases} 1 & \text{if } 0 < \text{Pass}(y_{\text{pred}}, \text{Tests}(x)) < 1, \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

Table 1: Test set accuracy for Qwen2.5-3B-Instruct with and without self-play and comparison to the format reward baseline. The Qwen2.5-Coder-3B-Instruct model is used for coding. The best results are indicated in bold and the results show standard deviations across three training runs.

	Multiplication	**Lin. Eqns.**	**Codeforces**
Qwen2.5-(Coder)-3B-Instruct	0.791	0.440	0.320
+ self-play	$\mathbf{0.948 \pm 0.009}$	$\mathbf{0.600 \pm 0.010}$	$\mathbf{0.391 \pm 0.019}$
+ self-play (format reward)	0.826 ± 0.079	0.553 ± 0.015	N/A

5 Experiments

5.1 Setups

Arithmetic. We prompt the proposer to generate a three-digit arithmetic problem and use the proposed problem as the input to the solver. The solver is trained via majority voting reward (Zuo et al., 2025) to reinforce the majority answer. The proposer reward is 1 if the problem is not too difficult (the majority answer only appears once, which means all the samples are different) and not too easy (the majority answer is equal to the number of samples N, which means all the samples were the same), and 0 otherwise. To evaluate the arithmetic ability of the model, we procedurally generate a test set of 4096 three-digit multiplication problems following the setup from TinyZero [1]. We run our experiments with Qwen2.5-3B-Instruct.

Algebra. We prompt the proposer to generate algebra word problems that involve linear equations with up to two variables. The solver and proposer rewards are the same as in the Arithmetic setup. For evaluation, we use the 100-question linear equation test set from the OMEGA benchmark (Sun et al., 2025). We run our experiments with Qwen2.5-3B-Instruct.

Coding. We prompt the proposer to generate programming problems similar in style and difficulty to LeetCode easy problems that take in a list of integers and output either a single integer or another list. Unlike in the Arithmetic and Algebra setups, the proposer is also asked to generate five unit tests, and the solver reward is the fraction of unit tests that it passes (0, 0.2, 0.4, 0.6, 0.8, or 1). The proposer reward is 1 if the solver reward is not either 0 or 1, which would indicate that the problem is either too easy or too difficult. To evaluate the coding ability of the model, we evaluate on a subset of the Codeforces[2] test set. containing 123 examples (specifically, the ones from the Eurus-2 (Cui et al., 2025) dataset). We run our experiments with Qwen2.5-Coder-3B-Instruct.

[1]https://github.com/Jiayi-Pan/TinyZero

[2]https://huggingface.co/datasets/MatrixStudio/Codeforces-Python-Submissions

Table 2: Samples from the model over the course of training for the Arithmetic task. The model gradually generates more challenging problems, without making them excessively difficult.

(Step 0) Proposer	$563 + 247 - 189$
(Step 0) Solver	`<think>` Let's break down the problem step by step: First, add 563 and 247: - $563 + 247 = 810$ Next, subtract 189 from the result: - $810 - 189$ To perform $810 - 189$, I will subtract the numbers step by step: - Subtract the units place: $0 - 9$, so we need to borrow 1 from the tens place. - After borrowing, this becomes $10 - 9 = 1$. - Now, the tens place value reduces by 1 (from 1 to 0), and we bring down the next digit (8). Since $0 - 8$ is not possible, we borrow 1 from the hundreds place. - After borrowing, this becomes $10 - 8 = 2$. - Now the hundreds place reduces by 1 (from 8 to 7), and we subtract: $7 - 1 = 6$. Putting it together, we get $810 - 189 = 621$. `</think>` `<answer>` 621 `</answer>`
(Step 10) Proposer	$673 - 145 + 98 \times 2 \div 7$
(Step 10) Solver	Let's solve the arithmetic problem step by step. `<think>` First, we need to follow the order of operations (PEMDAS/BODMAS rules), which stands for Parentheses/Brackets, Exponents/Orders, Multiplication and Division from left to right, Addition and Subtraction from left to right. The expression is $673 - 145 + 98 \times 2 \div 7$. 1. Calculating the Multiplication and Division: - First, perform $98 \times 2 = 196$ - Then, $196 \div 7 = 28$ Now the expression simplifies to: $673 - 145 + 28$ 2. Perform Addition and Subtraction (left to right): - $673 - 145 = 528$ - $528 + 28 = 556$ `</think>` `<answer>` 556 `</answer>`
(Step 20) Proposer	$384 \div (52 \times 2) + 7^3 - 111$
(Step 20) Solver	`<think>` Let's solve the expression step by step: 1. Evaluate the parentheses: $52 \times 2 = 104$ 2. Now the expression becomes: $384 \div 104 + 7^3 - 111$ 3. Perform the division: $384 \div 104 \approx 3.69$; taking integer part gives 3 4. Now we have: $3 + 343 - 111$ since $7^3 = 343$ 5. Perform the addition and subtraction: $3 + 343 = 346$, $346 - 111 = 235$ `</think>` `<answer>` 235 `</answer>`

5.2 Main Results

Table 1 shows results on the respective test sets for Arithmetic, Algebra, and Coding. Without *any external data*, we can improve the accuracy of Qwen2.5-3B-Instruct by 14% on Arithmetic and 16% on Algebra, of Qwen2.5-Coder-3B-Instruct by 7% on Coding. Furthermore, we also compare to a format reward baseline, which gives a reward of 1 to the solver if the format is correct and 0 otherwise (i.e., only teaches correct formatting), instead of the majority voting reward. The results show a significant performance improvement over this baseline, which indicates that these are genuine gains in reasoning ability and the model is not merely learning to format the answer correctly. The format reward is pertinent to Arithmetic and Algebra since the model is expected to put its final numerical answer in a specific format, but is not relevant for coding since the expected solution is long-form text. We show additional results with Llama models in the Appendix.

Table 3: Test set accuracy for self-play with various proposer update frequencies. The best results are indicated in bold and the results show standard deviations across three training runs.

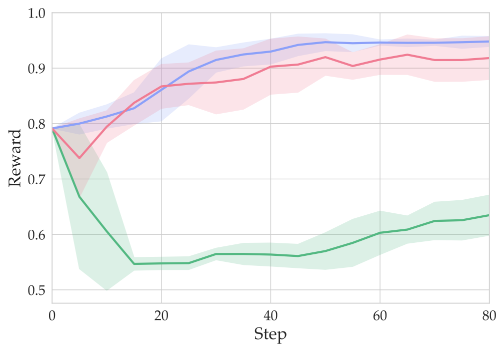
	Multiplication	**Lin. Eqns.**	**Codeforces**
Qwen2.5-(Coder)-3B-Instruct	0.791	0.440	0.320
frequency = 1	0.937 ± 0.019	0.556 ± 0.051	0.375 ± 0.050
frequency = 5	0.948 ± 0.009	$\mathbf{0.600 \pm 0.010}$	$\mathbf{0.391 \pm 0.019}$
frequency = 10	$\mathbf{0.951 \pm 0.012}$	0.546 ± 0.005	0.324 ± 0.014
frequency = ∞ (never)	0.934 ± 0.025	0.563 ± 0.023	0.343 ± 0.022

5.3 Qualitative Samples

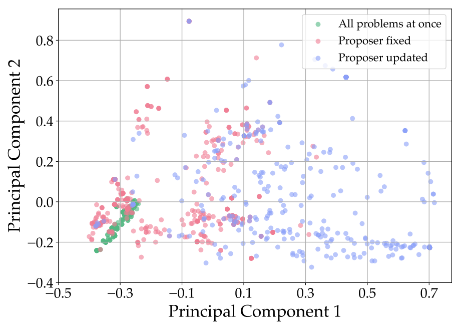
In this subsection, we study the qualitative behavior of the model. Table 2 shows samples from the Arithmetic task. At step 0, the model outputs a simple arithmetic problem $563 + 247 - 189$, but due to the proposer update, it learns to gradually increase the difficulty of its problems. At step 10, it generates $673 - 145 + 98 \times 2 \div 7$, and at step 20, it generates $384 \div (52 \times 2) + 7^3 - 111$. These arithmetic problems have more terms and involve more combinations of arithmetic expressions, so the model must improve its reasoning abilities in order to solve them. Although the test set consists only of three-digit multiplication problems, training on a wide diversity of self-generated problems is indeed beneficial. Note that we slightly edited the responses for brevity and readability. For more qualitative samples, see the Appendix.

5.4 Proposer Update Frequency

A key hyperparameter in our approach is how often to update the proposer. If it is never updated or updated infrequently, then the model might not learn to generate interesting enough problems. If it is updated too often, the solver might not have enough of a chance to improve on each set of problems and training might be unstable. We study this in Table 3, which shows the performance as we varied the update frequency of the proposer. Overall, we found that updating it every 5 steps worked well across all of our evaluation setups – a good balance between encouraging the proposer to generate more interesting problems and still allowing the solver to make progress. Furthermore, updating the proposer every 5 or 10 steps results in lower variance across runs.



(a) Learning curve comparison



(b) PCA plot comparison

Figure 2: Comparison of generating all problems at once vs one at a time using the proposer.

5.5 Encouraging Data Diversity

A key consideration when asking the model to generate its own data is how to encourage diversity. In our primary approach, we generate a single problem at each step using the proposer, and we find that this incremental strategy is sufficient to maintain diversity throughout training. As an alternative, we also explored generating all problems prior to training. Specifically, we generated 16 problems per inference call (to prevent the context length from being too large) and repeated this procedure 400 times, yielding a dataset of 6,400 questions. In this setup, we explicitly instructed the model via prompting to ensure that the generated problems spanned a wide range of difficulty, from easy to hard. However, as shown in Figure 2, this pre-generated dataset leads to a noticeable reduction in diversity, ultimately impairing learning on the Arithmetic task. To better understand this phenomenon, we further analyzed the generated questions using PCA. This visualization revealed that problems generated online with proposer updates exhibit substantially greater diversity compared to those produced via pre-generation. We hypothesize that this gap arises because models may struggle to reliably operationalize abstract instructions such as “generate diverse” or “generate difficult” purely from prompting. Instead, they appear to benefit from a quantitative and adaptive notion of difficulty provided by the asymmetric self-play process, which continuously refines the proposer’s problem distribution in response to the solver’s capabilities.

6 Limitations and Future Work

A central limitation of our approach is that we do not eliminate hand-engineering completely, particularly in the construction and refinement of the prompt for a specific topic. While our method requires less manual intervention compared to traditional systems, it does not eliminate prompt design entirely. In practice, we found that prompt iteration was necessary to constrain the generation space appropriately and to ensure that outputs adhered to our expected formatting. This was especially evident in the code generation task, where it was tricky to encourage the model to produce unit tests in an easy format to parse. Although we avoided extensive tuning to preserve generality as much as possible, even minimal manual iteration introduces a bottleneck and potential source of bias. In the future, one could automate this process, potentially through meta-learning, so that the system can autonomously evolve its own prompting strategy in response to downstream task feedback. Furthermore, currently there is no safeguard on the model-generated questions to ensure that they are reasonable, safe, relevant, or interesting. A promising avenue of future might work might be to prompt the LLM to filter or score responses by these characteristics. By constraining the questions in this way, it would be more feasible to scale fully self-supervised approaches. In addition, our method, like all unsupervised approaches, is fundamentally constrained by the absence of ground-truth rewards or perfect verifiers. In the absence of labeled data, the model must rely solely on internal heuristics, such as self-consistency or majority voting, to assess correctness. This introduces a risk of reinforcement of systematic errors: if the model repeatedly converges on an incorrect solution that is internally self-consistent, there is no mechanism for correction without external guidance. One possible direction to address this limitation is to incorporate existing labeled datasets in a semi-supervised setting to regularize the learning process.

7 Conclusion

This work presents a step toward more autonomous language model refinement by introducing a self-improving framework that requires no curated training data. Our method leverages the intrinsic capabilities of large language models by casting them in dual roles of proposer and solver within an asymmetric self-play setup. By rewarding the generation of problems that are neither too easy nor too difficult, and by reinforcing answers via internal agreement or external verification, we demonstrate that models can meaningfully improve their reasoning skills through interaction with self-generated content alone. Our experiments across arithmetic, algebra, and code generation tasks show that language models can bootstrap stronger problem-solving capabilities without any access to labeled data. This framework challenges the traditional paradigm that post-training must rely on human-curated datasets, and instead opens a path for fully self-supervised model learning. Our method is not without limitations: prompt design remains a source of hand-engineering, and without any external grounding, models can reinforce their own errors. Addressing these issues, perhaps through autonomous prompt optimization or the incorporation of small-scale supervision, offers promising directions for future research. Our findings suggest that large language models can be more than passive learners: they can be active agents in their own training loops. This reframing holds significant implications for the autonomy of future AI systems.

References

Yuri Burda, Harrison Edwards, Amos Storkey, and Oleg Klimov. Exploration by random network distillation. *arXiv preprint arXiv:1810.12894*, 2018.

Ganqu Cui, Lifan Yuan, Zefan Wang, Hanbin Wang, Wendi Li, Bingxiang He, Yuchen Fan, Tianyu Yu, Qixin Xu, Weize Chen, et al. Process reinforcement through implicit rewards. *arXiv preprint arXiv:2502.01456*, 2025.

Adrien Ecoffet, Joost Huizinga, Joel Lehman, Kenneth O Stanley, and Jeff Clune. Go-explore: a new approach for hard-exploration problems. *arXiv preprint arXiv:1901.10995*, 2019.

Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948*, 2025.

Jingcheng Hu, Yinmin Zhang, Qi Han, Daxin Jiang, Xiangyu Zhang, and Heung-Yeung Shum. Open-reasoner-zero: An open source approach to scaling up reinforcement learning on the base model. *arXiv preprint arXiv:2503.24290*, 2025.

Aviral Kumar, Vincent Zhuang, Rishabh Agarwal, Yi Su, John D Co-Reyes, Avi Singh, Kate Baumli, Shariq Iqbal, Colton Bishop, Rebecca Roelofs, et al. Training language models to self-correct via reinforcement learning. *arXiv preprint arXiv:2409.12917*, 2024.

Jia Li, Edward Beeching, Lewis Tunstall, Ben Lipkin, Roman Soletskyi, Shengyi Huang, Kashif Rasul, Longhui Yu, Albert Q Jiang, Ziju Shen, et al. Numinamath: The largest public dataset in ai4maths with 860k pairs of competition math problems and solutions. *Hugging Face repository*, 13:9, 2024.

Hao Liu and Pieter Abbeel. Behavior from the void: Unsupervised active pre-training. *Advances in Neural Information Processing Systems*, 34:18459–18473, 2021.

Mickel Liu, Liwei Jiang, Yancheng Liang, Simon Shaolei Du, Yejin Choi, Tim Althoff, and Natasha Jaques. Chasing moving targets with online self-play reinforcement learning for safer language models. *arXiv preprint arXiv:2506.07468*, 2025a.

Zhengzhong Liu, Bowen Tan, Hongyi Wang, Willie Neiswanger, Tianhua Tao, Haonan Li, Fajri Koto, Yuqi Wang, Suqi Sun, Omkar Pangarkar, et al. Llm360 k2: Building a 65b 360-open-source large language model from scratch. *arXiv preprint arXiv:2501.07124*, 2025b.

Zichen Liu, Changyu Chen, Wenjun Li, Penghui Qi, Tianyu Pang, Chao Du, Wee Sun Lee, and Min Lin. Understanding r1-zero-like training: A critical perspective. *arXiv preprint arXiv:2503.20783*, 2025c.

Lin Long, Rui Wang, Ruixuan Xiao, Junbo Zhao, Xiao Ding, Gang Chen, and Haobo Wang. On llms-driven synthetic data generation, curation, and evaluation: A survey. *arXiv preprint arXiv:2406.15126*, 2024.

Xueguang Ma, Qian Liu, Dongfu Jiang, Ge Zhang, Zejun Ma, and Wenhu Chen. General-reasoner: Advancing llm reasoning across all domains. *arXiv preprint arXiv:2505.14652*, 2025.

Mihai Nadas, Laura Diosan, and Andreea Tomescu. Synthetic data generation using large language models: Advances in text and code. *arXiv preprint arXiv:2503.14023*, 2025.

OpenAI OpenAI, Matthias Plappert, Raul Sampedro, Tao Xu, Ilge Akkaya, Vineet Kosaraju, Peter Welinder, Ruben D'Sa, Arthur Petron, Henrique P d O Pinto, et al. Asymmetric self-play for automatic goal discovery in robotic manipulation. *arXiv preprint arXiv:2101.04882*, 2021.

Deepak Pathak, Pulkit Agrawal, Alexei A Efros, and Trevor Darrell. Curiosity-driven exploration by self-supervised prediction. In *International conference on machine learning*, pp. 2778–2787. PMLR, 2017.

Mihir Prabhudesai, Lili Chen, Alex Ippoliti, Katerina Fragkiadaki, Hao Liu, and Deepak Pathak. Maximizing confidence alone improves reasoning. *arXiv preprint arXiv:2505.22660*, 2025.

Yuxiao Qu, Tianjun Zhang, Naman Garg, and Aviral Kumar. Recursive introspection: Teaching language model agents how to self-improve. *Advances in Neural Information Processing Systems*, 37:55249–55285, 2024.

Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D Manning, Stefano Ermon, and Chelsea Finn. Direct preference optimization: Your language model is secretly a reward model. *Advances in Neural Information Processing Systems*, 36:53728–53741, 2023.

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.

Ramanan Sekar, Oleh Rybkin, Kostas Daniilidis, Pieter Abbeel, Danijar Hafner, and Deepak Pathak. Planning to explore via self-supervised world models. In *International conference on machine learning*, pp. 8583–8592. PMLR, 2020.

Rulin Shao, Shuyue Stella Li, Rui Xin, Scott Geng, Yiping Wang, Sewoong Oh, Simon Shaolei Du, Nathan Lambert, Sewon Min, Ranjay Krishna, et al. Spurious rewards: Rethinking training signals in rlvr. *arXiv preprint arXiv:2506.10947*, 2025.

Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, YK Li, Y Wu, et al. Deepseekmath: Pushing the limits of mathematical reasoning in open language models. *arXiv preprint arXiv:2402.03300*, 2024.

Guangming Sheng, Chi Zhang, Zilingfeng Ye, Xibin Wu, Wang Zhang, Ru Zhang, Yanghua Peng, Haibin Lin, and Chuan Wu. Hybridflow: A flexible and efficient rlhf framework. *arXiv preprint arXiv: 2409.19256*, 2024.

Avi Singh, John D Co-Reyes, Rishabh Agarwal, Ankesh Anand, Piyush Patil, Xavier Garcia, Peter J Liu, James Harrison, Jaehoon Lee, Kelvin Xu, et al. Beyond human data: Scaling self-training for problem-solving with language models. *arXiv preprint arXiv:2312.06585*, 2023.

Yuda Song, Hanlin Zhang, Carson Eisenach, Sham Kakade, Dean Foster, and Udaya Ghai. Mind the gap: Examining the self-improvement capabilities of large language models. *arXiv preprint arXiv:2412.02674*, 2024.

Yiyou Sun, Shawn Hu, Georgia Zhou, Ken Zheng, Hannaneh Hajishirzi, Nouha Dziri, and Dawn Song. Omega: Can llms reason outside the box in math? evaluating exploratory, compositional, and transformative generalization. *arXiv preprint arXiv:2506.18880*, 2025.

Yanming Wan, Jiaxing Wu, Marwa Abdulhai, Lior Shani, and Natasha Jaques. Enhancing personalized multi-turn dialogue with curiosity reward. *arXiv preprint arXiv:2504.03206*, 2025.

Ke Wang, Jiahui Zhu, Minjie Ren, Zeming Liu, Shiwei Li, Zongye Zhang, Chenkai Zhang, Xiaoyu Wu, Qiqi Zhan, Qingjie Liu, et al. A survey on data synthesis and augmentation for large language models. *arXiv preprint arXiv:2410.12896*, 2024.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837, 2022.

Qiying Yu, Zheng Zhang, Ruofei Zhu, Yufeng Yuan, Xiaochen Zuo, Yu Yue, Tiantian Fan, Gaohong Liu, Lingjun Liu, Xin Liu, et al. Dapo: An open-source llm reinforcement learning system at scale. *arXiv preprint arXiv:2503.14476*, 2025a.

Tianyu Yu, Bo Ji, Shouli Wang, Shu Yao, Zefan Wang, Ganqu Cui, Lifan Yuan, Ning Ding, Yuan Yao, Zhiyuan Liu, et al. Rlpr: Extrapolating rlvr to general domains without verifiers. *arXiv preprint arXiv:2506.18254*, 2025b.

Eric Zelikman, Yuhuai Wu, Jesse Mu, and Noah Goodman. Star: Bootstrapping reasoning with reasoning. *Advances in Neural Information Processing Systems*, 35:15476–15488, 2022.

Xuandong Zhao, Zhewei Kang, Aosong Feng, Sergey Levine, and Dawn Song. Learning to reason without external rewards. *arXiv preprint arXiv:2505.19590*, 2025.

Xiangxin Zhou, Zichen Liu, Anya Sims, Haonan Wang, Tianyu Pang, Chongxuan Li, Liang Wang, Min Lin, and Chao Du. Reinforcing general reasoning without verifiers. *arXiv preprint arXiv:2505.21493*, 2025.

Yuxin Zuo, Kaiyan Zhang, Shang Qu, Li Sheng, Xuekai Zhu, Biqing Qi, Youbang Sun, Ganqu Cui, Ning Ding, and Bowen Zhou. Ttrl: Test-time reinforcement learning. *arXiv preprint arXiv:2504.16084*, 2025.

Adam Zweiger, Jyothish Pari, Han Guo, Ekin Akyürek, Yoon Kim, and Pulkit Agrawal. Self-adapting language models. *arXiv preprint arXiv:2506.10943*, 2025.

A Appendix

A.1 Implementation Details

We build our implementation on top of verl (Sheng et al., 2024). A list of hyperparameters can be found in Table 4. For all experiments, we report the best test accuracy achieved over 100 training steps, averaged over three training runs.

Table 4: Hyperparameters of SQLM.

Hyperparameter	**Value**
Max prompt length	512
Max response length	1024 (Arithmetic) 3072 (Algebra) 512 (Coding)
Batch size	64
Policy mini batch size	32
Policy micro batch size per GPU	8
Learning rate	1×10^{-6}
Weight decay	0.01
Learning rate warmup	Constant
Optimizer	Adam
Temperature	1.0
Top k	-1
Top p	1
Number of samples per example n	4
Remove padding	True
Use KL loss	True
KL loss coefficient	0.001
Clip ratio	0.2
Grad clip	1.0
Proposer update frequency	5

A.2 More Results

We use Qwen2.5-3B-Instruct for our experiments as it is a small model which still has strong math and coding capabilities, as well as good instruction-following capabilities (to enable the proposer to generate reasonable questions). To show the generality of our asymmetric self-play framework, we also show results with Llama-3.2-3B-Instruct and Llama-3.1-8B-Instruct on Codeforces in Table 5.

Table 5: Test set accuracy for Qwen2.5-Coder-3B-Instruct, Llama-3.2-3B-Instruct, and Llama-3.1-8B-Instruct, with and without self-play. The best results are indicated in bold and the results show standard deviations across three training runs.

	Codeforces
Qwen2.5-Coder-3B-Instruct	0.320
+ self-play	$\mathbf{0.391 \pm 0.019}$
Llama-3.2-3B-Instruct	0.211
+ self-play	$\mathbf{0.243 \pm 0.026}$
Llama-3.1-8B-Instruct	0.231
+ self-play	$\mathbf{0.382 \pm 0.023}$

A.3 Prompts

The prompts used for each task are shown in Table 6. For the Algebra task, we additionally encouraged diversity by asking the model to generate three problems and selecting the last one. For the Coding task, we generated random numbers to show the model the expected format for the test cases. This was done only to make processing of the inputs and outputs easier in the loop, and we intentionally did not give an example problem in order to not bias the proposer.

Table 6: Prompts used for each task.

Arithmetic	"""Generate a three-digit arithmetic problem (up to three digits). Make sure the numbers are not similar and appear unpredictable. Do not solve the problem."""
Algebra	"""Create three diverse, challenging algebra word problems that involve linear equations with up to two variables. Use only integers for all coefficients . The problem should be solvable with a unique solution where each variable has a rational (integer or fractional) value. Do not solve the problems. Then select the last one and put it in the format: Selected Question: <question>"""
Coding	"""Generate an original programming problem similar in style and difficulty to LeetCode easy problems. Requirements: - The problem must take a single line of space-separated integers as input and produce either a single integer or a space-separated list of integers as output. - Provide 5 test cases in the exact format: INPUT_STRING ||| OUTPUT_STRING (no explanations, no extra text, OUTPUT_STRING must include the trailing '\\n' if needed). Example Output Format: Problem Description: You are given a list of integers. Write a program that reads the list and returns <expected output>. Input: A single line contains space-separated integers a_1, a_2, ..., a_n (-1000 <= a_i <= 1000). Output: Print a single integer <expected output>. Test Cases: 8 -3 7 0 2 ||| 14 -2 5 -4 3 ||| 2 10 -10 ||| 0 4 ||| 4 -5 -1 -4 ||| -10"""

A.4 More Qualitative Samples

See Table 7 for samples from the Coding task. As training progresses, the model learns to generate more interesting and complex problems. In the beginning, it generates very easy problems which can be solved in one line, such as squaring each element of a list. However, at step 20, it learns to generate an interesting problem of finding the longest contiguous subarray with unique elements. Although we constrained the model to generate problems where the input is a list, one could imagine that this approach could generalize to a wider range of data structures and algorithms.

Table 7: Samples from the model over the course of training for the Coding task. The model gradually generates more challenging problems, without making them excessively difficult.

(Step 0) Proposer

You are given a list of integers. Write a program that reads the list and returns a new list containing the square of each integer in the original list.

(Step 0) Solver

```
# Read input from the user
input_string = input()
# Split the input string into a list of strings
input_list = input_string.split()
# Convert each string to an integer and store in a list
int_list = list(map(int, input_list))
# Calculate the square of each integer
squared_list = [x**2 for x in int_list]
# Print the squared list as a space-separated string
print(' '.join(map(str, squared_list)))
```

(Step 10) Proposer

You are given a list of integers. Write a program that reads the list and returns the sum of all the even numbers in the list.

(Step 10) Solver

```
# Read the input line of integers
input_line = input().split()
# Initialize the sum of even numbers
sum_even = 0
# Iterate over each integer in the input list
for number in input_line:
    # Convert the string number to an integer
    num = int(number)
    # Check if the number is even
    if num % 2 == 0:
        # Add the even number to the sum
        sum_even += num
# Print the sum of even numbers
print(sum_even)
```

(Step 20) Proposer

You are given a list of integers. Write a program that reads the list and returns the length of the longest contiguous subarray with all unique elements.

(Step 20) Solver

```
def longest_unique_subarray(nums):
    # Initialize variables to track the maximum length and the current start index
    max_length = 0
    current_start = 0
    # Dictionary to store the last seen index of each element
    last_seen = {}
    # Iterate through the list with the current index as end
    for current_end, num in enumerate(nums):
        # If the element is seen and the last seen index is greater than or equal to the current start
        if num in last_seen and last_seen[num] >= current_start:
            # Move the start index to one position ahead of the last seen index of the current element
            current_start = last_seen[num] + 1
        # Update the last seen index of the current element
        last_seen[num] = current_end
        # Update the maximum length if the current subarray is longer
        max_length = max(max_length, current_end - current_start + 1)
    # Return the length of the longest subarray with unique elements
    return max_length
# Read the input and convert it to a list of integers
input_list = list(map(int, input().split()))
# Call the function and print the result
print(longest_unique_subarray(input_list))
```