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Deep Seek AI

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ABSTRACT

DeepSeek AI is an advanced artificial intelligence designed to solve very difficult data analysis challenges in many sectors. Its primary aim is to provide doable insights that speed up decision-making processes and improve operational efficiencies, for which DeepSeek AI applies machine-learning algorithms, natural language processing (NLP), and predictive analytics. In this paper, we investigate the architecture, applications, advantages, and ethical aspects of DeepSeek AI, which is seen as a change agent for industries such as healthcare, finance, and environmental science.

1. INTRODUCTION

In recent times, post-training has become the crucial last step in training from start to finish. demonstrated boost correctness, correspond to Evidence for the assertion that reasoning capabilities were first injected into OpenAI's o1 (OpenAI, 2024b) series models by inferencing time scaling, stretching the length of the Chain-of-Thought reasoning processes, has yielded marked improvements in many reasoning tasks, whereby mathematics, coding, and scientific reasoning find themselves among the benefiting varieties. Yet, the problem of effective test-time scaling remains a hotly debated topic in the major circles of research. Much prior work has investigated many avenues, such as process-based reward models (Lightman et al., 2023; Uesato et al., 2022;Wang et al., 2023), reinforcement learning (Kumar et al., 2024), search algorithms like Monte Carlo Tree Search and Beam Search (Feng et al., 2024; Trinh et al., 2024; Xin et al., 2024), but with no candidate so far offering general reasoning abilities on par with those provided by OpenAI's o1 series models.

We investigate also distilling from DeepSeek-R1 into a smaller dense model. Using Qwen2.5-32B (Qwen, 2024b) as a base model, direct distillation from DeepSeek-R1 shows better performance than applying RL on it. This indicates the importance of the reasoning patterns that the larger base models have learned as an enhancement to reasoning. We will also release Qwen and Llama (Dubey et al., 2024) as open-source. Interestingly, our distilled 14B model beats the current best open-source QwQ-32B-Preview (Qwen, 2024a) by quite a large margin while the distilled 32B and 70B set a new record on the reasoning benchmarks among dense models.

1. Contributions

We apply RL straight to the base model without any prior SFT. Thus, the model can begin to explore chain-of-thought (CoT) as the means to solve complex problems leading to the realization of DeepSeek-R1-Zero. DeepSeek-R1-Zero shows abilities leaving SFT aside. This offers the very first winks at future developments. preference and two SFT stages that act as seedlings Our belief is that the pipeline would be a great booster for creating better models within the industry.

2. Distillation

This quantifies that larger model reasoning can be distilled into smaller models for performance beyond RL-reasoned patterns obtained for mini models.

• A number of going models cencqv' fied by the research community were engaged in fine-tuning. As the evaluation results show, thus marking an advantage from QwQ-32B-Preview. On the other hand they are promising when compared to o1-mini. We will thus be open-sourcing distilled checkpoints.

3. Summary of Evaluation Results

Knowledge: gets a good score on these tests compared with DeepSeek-V3. For instance, it scored 90.8% on the MMLU test, on the, and the GPQA Diamond test. Though it came a little short in performance compared to OpenAI-o1-1217 in these tests, it has outperformed several other closed-source models, showing some competitive power, particularly concerning educational tasks. It has also shown to skillfully answer factual questions on the SimpleQA test, where DeepSeek-R1 defeats DeepSeek-V3 by another margin as in the above case for OpenAI-01 against 4o here. o Others: It performs really well with other tasks and even more on ArenaHard at 92.3%, showing its prowess toward a sensible treatment of non-exam-oriented questions massively. Long-context understanding is where DeepSeek-R1 nails it too, going far ahead.

4. Approach

4.1 Overview:

Earlier models were mostly based on predominant amounts of supervised data since this was thought to be necessary for enhancing performance. This paper argues that reasoning ability could also be greatly improved via large-scale RL training, even when no SFT is applied during cold-start initialization. To some degree, performance improvements can also be made with describe Furthermore, the reasoning power learned from DeepSeek-R1 will be distilled down to small dense models that we refer to as "Lightweights."

4.2 Reward Modelling:

Rewards are considered the training signals from which RL derives its optimization directions. In the case of consisting mostly of correctness. compiler-based feedback produced from certain test cases. o Format Rewards: More specifically, applied a format

display its reasoning between the tags "think" and "think". The outcome or the process may suffer from reward hacking in a large-scale reinforcement learning process, and retraining the reward model imposes more costs and complexity on the entire training pipeline.

4.3 Training Template

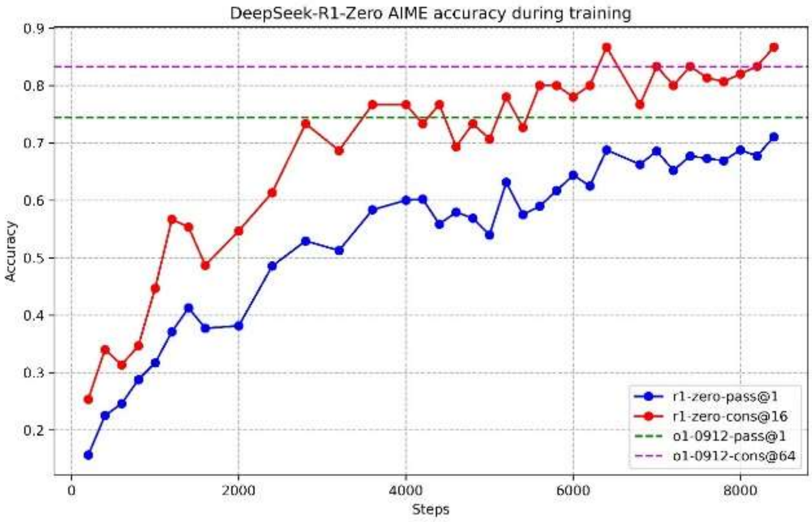
DeepSeek-R1-Zero starts off with the design of a simple template instructing the base model to follow specific instructions laid out by us. This template, as shown. With that being said, we want to keep our constraining instructions limited in format, with no requiring specific strategies.

4.4 Performance, Self-evolution Process

DeepSeek-R1-Zero Performance The performance history of DeepSeek is shown in Figure 2, starting from the RL training phase until the evaluation against the AIME 2024 benchmark. The graph depicts sustained and steady improvement in performance of DeepSeek-R1-Zero during the course of RL training process. Very importantly, DeepSeek-R1-Zero has shown a significant increase in performance, which an average of only 15.6 to an astounding 71.0%. DeepSeek-R1-Zero finally reaches the level of performance of OpenAI-o1-0912. This tremendous increase further demonstrates the effectiveness of our RL algorithm in enhancing the performance of the model. in a view of Table 2, a performance comparison between those two models was carried out against reasoning-related benchmarks. The results show that RL drives.

Model	AIME 2024		MATH-500	GPQA Diamond	LiveCode Bench	CodeForces
	pass@1	cons@64	pass@1	pass@1	pass@1	rating
OpenAI-o1-mini	63.6	80.0	90.0	60.0	53.8	1820
OpenAI-o1-0912	74.4	83.3	94.8	77.3	63.4	1843
DeepSeek-R1-Zero	71.0	86.7	95.9	73.3	50.0	1444

Table 1 | Comparison of DeepSeek and OpenAI



Deep Seek achieves strong capacity requiring .which is nothing less than a watershed moment again because it shows that the model learns and generalizes well through RL alone. Majority voting can, in fact, boost the performance of DeepSeek-R1-Zero even further: e.g., majority voting .Then RL is run directly off the base model; hence, the model's progress can be closely observed, independent of the supervised fine-tuning stage. In this way, an uninterrupted view of the model's evolution is won over time, particularly concerning the intricacy of reasoning tasks it can deal with.

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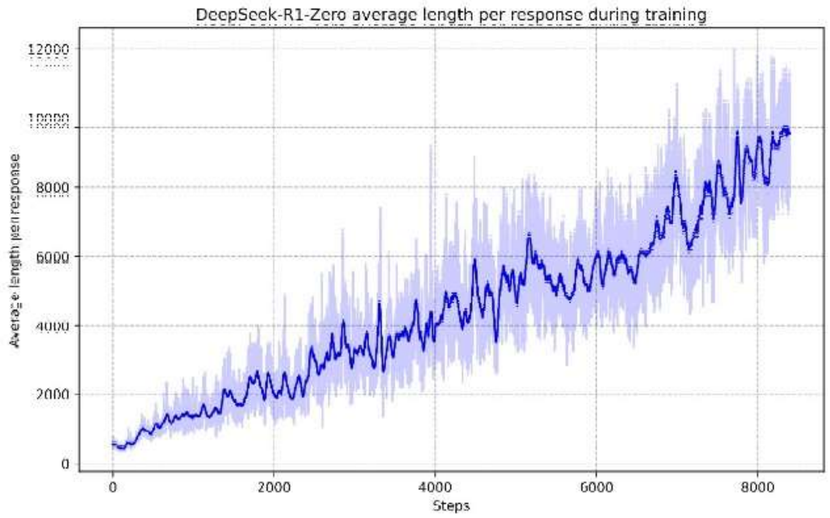

Neither of these amendments was an externalThe improvements DeepSeek-R1-Zero makes during training are intrinsic to its development. By computationalization during extended test time, the very nature of DeepSeek-R1-Zero is to evolve toward an increasingly complex task of reasoning in that window. The computation takes the form of process in a bigger way. Another wonder in the self-evolution-based approach is that as the test-time computation evolves, there begins the emergence of intelligent behaviors: reconsideration, reflection, where the model goes back to assess its options and dimensions of exploring other ways of problem-solving. Such behaviors are never coded, but emerge in enactment with the reinforcement learning environment. These spontaneous developments do even more wonders toward reasoning, allowing DeepSeek-R1-Zero to take more difficult assignments and to do so efficiently and accurately. another very interesting phenomenon short could be termed the "aha moment.” for thinking about a problem-iterating on the solution-to-be-found due to the earlier set of assignments. Such behavior not only signifies the strengthening of the model's , but it is also a charming illustration of the reinforcement learning process leading to sometimes wholly unanticipated and sophisticated effects. It is an "aha moment" not just for the model but also for the researchers tracking its behavior.

Question: If $a > 1$, then the sum of the real solutions of $\sqrt{a - \sqrt{a + x}} = x$ is equal to

Response: <think>
To solve the equation $\sqrt{a - \sqrt{a + x}} = x$, let's start by squaring both $\cdots$
$\left(\sqrt{a - \sqrt{a + x}}\right)^2 = x^2 \implies a - \sqrt{a + x} = x^2.$
Rearrange to isolate the inner square root term:
$(a - x^2)^2 = a + x \implies a^2 - 2ax^2 + (x^2)^2 = a + x \implies x^4 - 2ax^2 - x + (a^2 - a) = 0$
$\ldots$
Wait, wait. Wait. That's an aha moment I can flag here.
Let's reevaluate this step-by-step to identify if the correct sum can be $\cdots$
We started with the equation:
$\sqrt{a - \sqrt{a + x}} = x$
First, let's square both sides:
$a - \sqrt{a + x} = x^2 \implies \sqrt{a + x} = a - x^2$
Next, I could square both sides again, treating the equation: $\cdots$
$\ldots$

R1-Zero While the strong reasoning skills of DeepSeek-R1-Zero were demonstrated together with surprising and powerful reasoning behavior formed by the AI, it suffered from various issues. One of these issues is readability problems, such as language mixing. To allow more readability for reasoning processes and sharing them with an open community, we are looking into a possible second iteration, DeepSeek-R1, which uses reinforcement learning.

4.5 DeepSeek : Reinforcement Learning with Cold Start

Since DeepSeek-R1-Zero has shown promising results , an easy-to-use model that produces intuitively clear and coherent CoTs and displays answer set up described below.

4.5.1 Cold Start

In contrast to DeepSeek, in order to overcome, a small amount of long CoT data was constructed and collected for fine-tuning the model into an initial RL actor for DeepSeek-R1. This data was collected using the following strategies, instructing models to generate elaborate, collecting the outputs of post-processing.

• **Readability**: A major shortcoming Deep Seek is that often the readable; be lacking in markdown formatting that highlights answers for the user. On the contrary, Data Creation for

4.5.3 Rejection Sampling and Supervised Fine-Tuning

After running based RL to convergence, we collect SFT-based training data from a new checkpoint for the next round. In contrast to is primarily targeted at time we incorporate different improve formulate according to the following reasoning-through-action. Curated prompts as outlined above. Past collections relied entirely on rule-based reward assessment, whereas these latter ones are extended to include data conquered by generative reward assessment, with definite ground-truth on some occasions and model prediction queried on DeepSeek-V3 in others. Additionally, some of the chaotic model outputs are hard to read; hence we filter mixed-languages chain-of-thoughts out along with long paragraphs and code blocks. For every prompt, we sample multiple responses and keep only the good ones, making for around 600k reasoning-related training samples in all. On the non-reasoning side, we use the DeepSeek-V3 pipeline to collect an SFT dataset for DeepSeek-V3, including writing, factual QA, self-knowledge, and even translation. Non-reasoning samples that encroach on reasoning parameters are generated using DeepSeek-V3, which generates the CoT before being fed the prompt and asked to answer the question. The exception is for really simple prompts, appraising just an entry like, "hello," for which we do not provide a CoT. This brings our total to around 200k samples that are not about reasoning.

4.6 Distillation: Empower Small Models with Reasoning Capability

As detailed in ?2.3.3, the 800k samples curated with DeepSeek-R1 were used to fine-tune open-source models like Qwen (Qwen, 2024b) and Llama (AI@Meta, 2024) to endow smaller, more efficient models with reasoning capabilities like those of DeepSeek-R1. The evidence we found suggests that a very simple distillation technique can capability of smaller models considerably. The base models we experimented with were Instruct. Llama-3.3 was selected because of its somewhat better reasoning ability than without any RL stage, even if by delving into RL, one could achieve a big lift in performance on th here is to showcase the.

5. Experiment

Benchmark Such models are evaluated on multiple benchmarks such as the MMLU (Hendrycks et al., 2020), MMLU-Redux (Gema et al., 2024), MMLU-Pro (Wang et al., 2024), C-Eval (Huang et al., 2023), and CMMLU (Li et al., 2023), IFEval (Zhou et al., 2023), FRAMES (Krishna et al., 2024), GPQA Diamond (Rein et al., 2023), SimpleQA (OpenAI, 2024c), C-SimpleQA (He et al., 2024), SWE-Bench Verified (OpenAI, 2024d), Aider 1, LiveCodeBench (Jain et al., 2024) (2024-08 -2025-01), Codeforces 2, Chinese National High School Mathematics Olympiad (CNMO 2024)3, and American Invitational Mathematics Exam 2024 (AIME 2024)(MAA, 2024). Finally, in addition to conventional benchmarks, we also evaluate our models on open-ended generation tasks where models such as large language models are used as judges. Specifically, we'll track the original configurations of AlpacaEval 2.0 (Dubois et al., 2024) and Arena-Hard (Li et al., 2024), which utilize GPT-4-Turbo-1106 as judges for pairwise comparisons. last would be fed for evaluation in order to mitigate length bias. are benchmark evaluations on MMLU, DROP, GPQA Diamond, and SimpleQA are performed using prompts from the simpleevals framework. For MMLU-Redux, we adopt the prompt format of Zero-Eval (Lin, 2024) and implement it in a zero-shot setting. Regarding MMLU-Pro, C-Eval and CLUE-WSC, original prompts are given in few-shot cases, so a slight adjustment is made in the prompt setting to the zero-shot.

5.1 DeepSeek-R1 Evaluation

	Benchmark (Metric)	Claude-3.5-Sonnet-1022	GPT-4o 0513	DeepSeek V3	OpenAI o1-mini	OpenAI o1-1217	DeepSeek R1
	Architecture	-	-	MoE	-	-	MoE
	# Activated Params	-	-	37B	-	-	37B
	# Total Params	-	-	671B	-	-	671B
English	MMLU (Pass@1)	88.3	87.2	88.5	85.2	**91.8**	90.8
	MMLU-Redux (EM)	88.9	88.0	89.1	86.7	-	**92.9**
	MMLU-Pro (EM)	78.0	72.6	75.9	80.3	-	**84.0**
	DROP (3-shot F1)	88.3	83.7	91.6	83.9	90.2	**92.2**
	IF-Eval (Prompt Strict)	**86.5**	84.3	86.1	84.8	-	83.3
	GPQA Diamond (Pass@1)	65.0	49.9	59.1	60.0	**75.7**	71.5
	SimpleQA (Correct)	28.4	38.2	24.9	7.0	**47.0**	30.1
	FRAMES (Acc.)	72.5	80.5	73.3	76.9	-	**82.5**
	AlpacaEval2.0 (LC-winrate)	52.0	51.1	70.0	57.8	-	**87.6**
	ArenaHard (GPT-4-1106)	85.2	80.4	85.5	92.0	-	**92.3**
Code	LiveCodeBench (Pass@1-COT)	38.9	32.9	36.2	53.8	63.4	**65.9**
	Codeforces (Percentile)	20.3	23.6	58.7	93.4	**96.6**	96.3
	Codeforces (Rating)	717	759	1134	1820	**2061**	2029
	SWE Verified (Resolved)	**50.8**	38.8	42.0	41.6	48.9	49.2
	Aider-Polyglot (Acc.)	45.3	16.0	49.6	32.9	**61.7**	53.3
Math	AIME 2024 (Pass@1)	16.0	9.3	39.2	63.6	79.2	**79.8**
	MATH-500 (Pass@1)	78.3	74.6	90.2	90.0	96.4	**97.3**
	CNMO 2024 (Pass@1)	13.1	10.8	43.2	67.6	-	**78.8**
Chinese	CLUEWSC (EM)	85.4	87.9	90.9	89.9	-	**92.8**
	C-Eval (EM)	76.7	76.0	86.5	68.9	-	**91.8**
	C-SimpleQA (Correct)	55.4	58.7	**68.0**	40.3	-	63.7

Table 3|ComparisonbetweenDeepSeek-R1 and other representative models.

Various training and evaluation datasets and GPQA. Outperforming -V3, DeepSeek-R1 shows prominent performance in these educational benchmarks primarily due to its better performance in STEM question answering, where large-scale reinforcement learning plays a dramatic role in enhancing its performance. performs well on, further ability in. The potential of reasoning approaches -powered is hereby demonstrated outperformed, thus showing its ability in answering fact-based queries. A similar trend is observed for OpenAI-o1-superior-to- with respect to this benchmark. DeepSeek-R1 does, however, fare worse than DeepSeek-V3 on the Chinese SimpleQA benchmark as a consequence of an inclination to refuse answers to certain queries following safety reinforcement learning; in the absence of safety reinforcement learning, DeepSeek-R1 would be scoring above 70% accuracy.

6. Discussion

6.1 Distillation v/s Reinforcement Learning

It can be observed from the distilling of DeepSeek-R1 that this small model performs quite well. One remaining question is whether the model can using the large-scale RL training described in. We used math, code, and STEM data as inputs for the, yielding Based on the given in it can be concluded that this model of 32B, after the complete execution of large-scale;

Model	AIME 2024		MATH-500	GPQA Diamond	LiveCodeBench
	pass@1	cons@64	pass@1	pass@1	pass@1
QwQ-32B-Preview	50.0	60.0	90.6	54.5	41.9
DeepSeek-R1-Zero-Qwen-32B	47.0	60.0	91.6	55.0	40.2
DeepSeek-R1-Distill-Qwen-32B	**72.6**	**83.3**	**94.3**	**62.1**	**57.2**

parallelizes well on performance. demonstrates much greater efficacy while DeepSeek-R1-Zero-Qwen-32B fails across the benchmarks. Thus, this allows us to take away two conclusions good results, while s utilizing the massive- articulated will need immense be able to perform better than distillation itself. Second, distillation strategies may be cost-effective in their own right, but moving towards the other side of intelligence would require even stronger base models and wider scales of reinforcement learning.

6.2 Unsuccessful Attempts

The big failures and setbacks in the beginning stages of the DeepSeek-R1 development were also experienced. Some of our failure stories are shared here for insights, but by no means does that imply that such an approach cannot be used to develop great reasoning models. Process Reward Model (PRM) is a fair idea to steer the model toward better ways to solve reasoning tasks (Lightman et al., 2023; Uesato et al., 2022;Wang et al., 2023). That said, we observe three key limitations affecting its practical success. First, there is no rigorous criterion to explain challenging aspect is to assess the correctness of that intermediate step. Automated model-based annotations could struggle to produce good enough results, and manual ones just won't scale.

Monte Carlo Tree Search (MCTS) Further Inspired by AlphaGo (Silver et al., 2017b) and AlphaZero (Silver et al., 2017a), we investigated improving test-time compute scalability using Monte Carlo Tree Search (MCTS). The method inverts that walk through with some systematic approach. to output several tags that that need to be taken for the search. In training, we start with the gathered prompt from the user to find an answer via MCTS with the guidance of the training scaling for its application suffers from several difficulties. First, unlike chess, in which the modes of solutions to reach the goal are quite well-defined, token generation has exponentially many more modes. To remedy this, we allow for a maximum number of reasonable extensions per node, which value model influences the generation directly by steering every really tough and lowers the ability of the model to improve itself iteratively. While the very essence of AlphaGo's success comes from developing a value model that aids in boosting the performance, such an approach is quite difficult to implement in our case on account of the intricacy of token generation. To conclude, although MCTS would enhance performance at inference time in conjunction with a pre-trained value model, the possibility of iterative self-boosting of model performance through self-search faces monumental challenges.

7. Conclusion

Moving into distant intend concerning these following areas for Currently, DeepSeek-R1's capabilities lag far behind those of such aspects expect future investigations to find ways in which used domains further Currently, has been ,which might raise issues of language mixing while handling queries posed in different languages. For instance, when the queries are in a language other than English or Chinese, DeepSeek-R1 might still employ English for reasoning and replies. We will look into overcoming this in a further version. Prompting Engineering: While assessing to prompting, with few-shot prompting degrading, for best results, we suggest that task directly and specify the required. found little application in software engineering mainly due to long evaluation times, which affect the efficiency of the RL process. As a result, DeepSeek-R1 was not able to show significant -VIII on benchmarks. Future versions will remedy this by applying on the data.

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