Auto MC-Reward: Automated Dense Reward Design with Large Language Models for Minecraft

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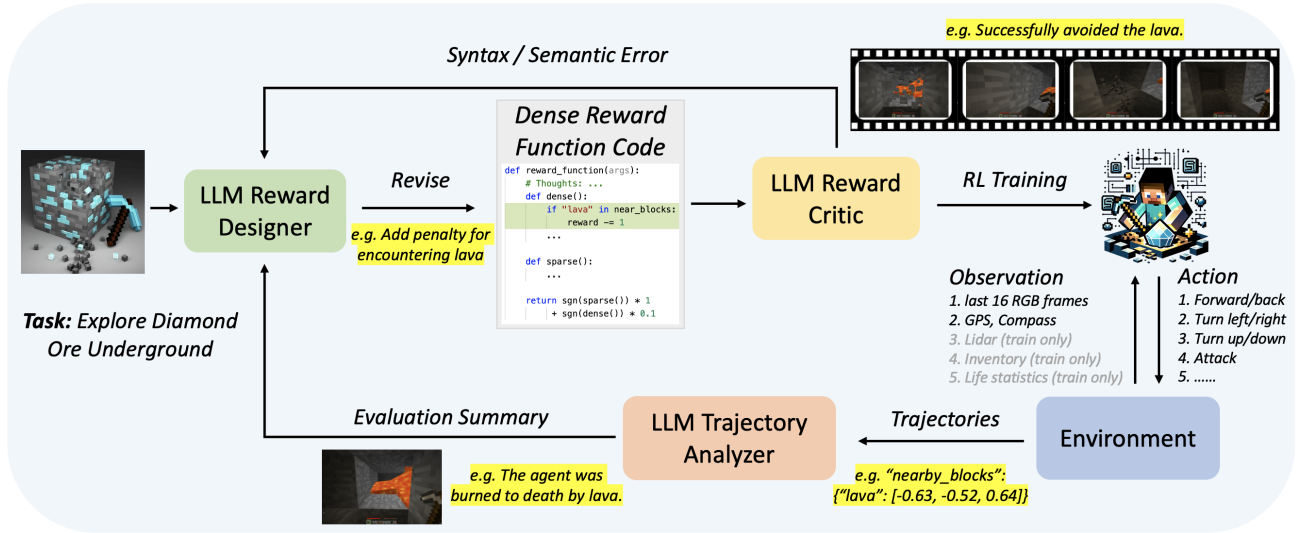https://yangxue0827.github.io/auto_mc-reward.html

Figure 1. Overview of our Auto MC-Reward. Auto MC-Reward consists of three key LLM-based components: Reward Designer, Reward Critic, and Trajectory Analyzer. A suitable dense reward function is iterated through the continuous interaction between the agent and the environment for reinforcement learning training of specific tasks, so that the model can better complete the task. An example of exploring diamond ore is shown in the figure: i) Trajectory Analyzer finds that the agent dies from lava in the failed trajectory, and then gives suggestion for punishment when encountering lava; ii) Reward Designer adopts the suggestion and updates the reward function; iii) The revised reward function passes the review of Reward Critic, and finally the agent avoids the lava by turning left.

Abstract

Traditional reinforcement-learning-based agents rely on sparse rewards that often only use binary values to indicate task completion or failure. The challenge in exploration efficiency makes it difficult to effectively learn complex tasks in Minecraft. To address this, this paper introduces an advanced learning system, named Auto MC-Reward, that leverages Large Language Models (LLMs) to automatically design dense reward functions, thereby enhancing the learning efficiency. Auto MC-Reward consists of three important components: Reward Designer, Reward Critic, and Trajectory Analyzer. Given the environment information and task descriptions, the Reward Designer first design the reward function by coding an executable Python function with predefined observation inputs. Then, our Reward Critic will be responsible for verifying the code, checking whether the code is self-consistent and free of syntax and semantic errors. Further, the Trajectory Analyzer summarizes possible failure causes and provides refinement suggestions according to collected trajectories. In the next round, Reward Designer will take further refine and iterate the dense reward function based on feedback. Experi-

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ments demonstrate a significant improvement in the success rate and learning efficiency of our agents in complex tasks in Minecraft, such as obtaining diamond with the efficient ability to avoid lava, and efficiently explore trees and animals that are sparse on the plains biome.

1. Introduction

Minecraft, as the world's best-selling game, offers a range of tasks from exploration, survival to creating. It has become an important environment for researching efficient Reinforcement Learning (RL) [15, 21]. In particular, its extreme sparsity of rewards and huge complexity of the decision space pose significant challenges for RL methods. Currently, the most effective learning strategy involves pre-training through behavior cloning [3], using learned behavioral priors to narrow the decision space. Nevertheless, it still requires billions of environmental interactions for effective learning due to the sparse reward nature of Minecraft.

On the other hand, previous researchers have proposed a variety of dense reward signals to enable efficient learning for specific sparse reward tasks [2, 26, 27, 34, 36]. However, their applicability on the complex and long-horizon tasks in Minecraft remains an open question. To deeply reveal the challenges in Minecraft, we examine on several representative challenging tasks, *e.g.* exploring underground for diamonds. We find that even after behavior cloning, most of these methods still fail to make significant progress on these tasks, further highlighting the difficulty of Minecraft and the limitations of existing dense reward methods.

It is noteworthy that for human players, Minecraft is a relatively simple casual game [11]. The advantage of human lies in their ability to summarize based on practice. For example, an accidental burning death from lava can teach human to avoid getting too close to it. Such summaries, based on life experience and practice, are key to human intelligence [39, 42]. Most existing RL methods overlook this ability. On the other hand, Large Language Models (LLMs) have recently demonstrated human-like common sense and reasoning capabilities [17, 35, 51]. We find that leveraging LLMs can help RL agents simulate the practice summarization abilities of human. Based on the historical action trajectories and success-failure signals of the agents, LLMs can automatically design and refine corresponding auxiliary rewards, effectively overcoming the sparse reward challenge in Minecraft.

According to above analysis, we propose an automated method named Auto MC-Reward, to design and improve auxiliary reward functions according to task descriptions and historical action trajectories. This method utilizes the task understanding and experience summarization abilities of LLMs, providing detailed and immediate rewards for

learning guidance. Specifically We first use LLMs to design task-related dense reward functions based on basic descriptions of the environment and tasks, named as Reward Designer. These reward functions are used to train agents after self-verification, *i.e.* Reward Critic. To address potential biases or oversights in LLM's understanding, we also propose a LLM-based Trajectory Analyzer to analyze and summarize collected trajectories from the trained agent, and automatically help Reward Designer to improve the reward functions.

We verify the effectiveness of Auto MC-Reward on a series of representative benchmarks, including horizontal exploration for diamonds underground and approaching trees and animals on the plains biome. Experiments show that Auto MC-Reward achieves significantly better results on these tasks compared to original sparse reward and existing dense reward methods, showing its advanced ability of empowering efficient learning on sparse reward tasks. By iteratively refining the design of rewards functions, Auto MC-Reward enables the agent to efficiently learn new behaviors that is beneficial to the corresponding tasks, *e.g.* avoiding lava, which greatly improves the success rate. Moreover, Auto MC-Reward achieves a high diamond obtaining success rate (36.5%) with only raw information, demonstrating its ability of solving long-horizon tasks.

2. Related Work

Minecraft Agents are intelligent agents designed to accomplish various tasks while playing the game Minecraft. Most of previous works adopt reinforcement learning for agent training. Due to the extremely sparse rewards and complex decision space of Minecraft tasks, early attempts have tried hierarchical RL [29, 33, 40, 41], curriculum learning [22], and imitation learning [1] to empower more efficient RL training. To narrow the decision space, recent work [3] build a foundation model by performing imitation on YouTube videos. DreamerV3 [16] instead learns a world model that explores the environment efficiently. As the LLMs demonstrate their general planning ability, a series of research [18, 45, 46, 50, 52] leverage LLMs as high-level planners that decompose long-term complex tasks as basic skills and implement the skills with RL agents or handcrafted scripts.

Auto MC-Reward aims to design dense rewards for Minecraft tasks automatically using LLMs, which is orthogonal to previous works on Minecraft agents that mainly focus on RL learning algorithms or high-level planning.

Efficient Learning in Sparse Reward Tasks is a long-standing challenge in reinforcement learning due to the lack of effective learning signals [25]. A common solution is to handcraft dense reward functions that provide intermediate reward signals based on human expertise, which requires

time-consuming trial-and-error for each environment and task. Another line of previous research focus on proposing general-purpose dense auxiliary reward functions, such as curiosity-driven exploration [6, 19, 27, 36], self-imitation learning [34], and goal-conditioned reinforcement learning [2, 23, 26, 44]. Despite the success on certain specific tasks, the applicability of these methods in the complex environment of Minecraft remains uncertain. Recent works [9, 10, 13, 30, 31] also propose to use pre-trained models to assign reward to intermediate states of completing tasks. However, these approaches produce reward values in a black-box manner, which cannot be interpreted and improved based on the experience of the agents, and the generalizability of these models on new tasks is not guaranteed.

In contrast, Auto MC-Reward automatically produces explainable reward functions according to the task descriptions. Moreover, the reward functions can be improved to be more precise based on the experience of the agent.

Automated Reward Function Design aims to find an optimal reward function that drives efficient reinforcement learning for interested tasks. Previous works [8, 14] employ evolutionary algorithm for searching optimal reward functions for specific tasks. Most of these attempts have a highly constrained search space that only adjusts parameters of task-specific handcrafted reward templates. Recently, a series of research [7, 10, 24, 28] employs LLMs for integrating human preference into open-domain tasks without clear completion criteria by directly prompting LLMs with environment trajectories and natural language task descriptions. The reward values are generated on-the-fly by LLMs, which is black-box and has heavy computational cost due to the nature of LLMs. In contrast, Auto MC-Reward employs LLMs to generate white-box code-form reward functions.

Concurrent works [32, 48, 49] also propose to use LLMs as a coder to generate reward functions for robotics control tasks. Different from these methods, Auto MC-Reward considers more complex Minecraft environments that has diverse scenarios and high uncertainty, requiring more precise and thorough reward designing.

3. Method

Auto MC-Reward consists of three components: Reward Designer, Reward Critic, and Trajectory Analyzer. Given the environment information and task descriptions, the Reward Designer proposes the reward function by coding an executable Python function with pre-defined observation inputs. The Reward Critic verifies if the proposed reward function is self-consistent and if it meets the format requirements. The designed reward function which passes the Reward Critic is used to train agents in the environment. To improve the designed reward function according to empiri-

cal experience, the Trajectory Analyzer is proposed to summarize possible failure causes and provide refinement suggestions on the reward function based on the inference trajectories of the trained agents. Then the Reward Designer modifies the reward function based on the feedback from Trajectory Analyzer. Figure 1 shows the overview of the Auto MC-Reward.

3.1. Reward Designer

We utilize a Reward Designer to generate the reward function code to provide intermediate instructive learning signals to the agent. It takes as input task descriptions, game information, and reward function requirements, generating reward functions in executable code form. When updating reward function, we also provide analysis of the agent's performance when interacting with the game environment. The input prompt is introduced in Section 4.2.

The generated reward function uses a pre-defined observation format as input. This includes the nearest distance of each block type within the visible range in the current and previous steps, changes in inventory between adjacent steps, health points, and the agent's location in each past step. These parameters can provide information on the agent's current and historical states, assisting the reward function in various situations.

Multi-Step Memory. Long-term tasks require the transfer of information across multiple steps. Thus, we introduce a multi-step memory mechanism. It is provided to Reward Designer as a empty dictionary at the beginning, and the reward function can save necessary data into the memory to be used in future steps. In the actual reward function of the explore-tree task, we observed that the agent records the distance to a tree at each step, thereby encouraging getting closer with the tree than the previous step.

Chain of Thought. We require the LLM to first describe its design thoughts, such as considering potential failure reasons and the details of the reward function design. These thoughts are to be written as comments at the beginning of the code. This is a mechanism similar to Chain of Thought (CoT) [47], where the thought process precedes the coding implementation. In the specific code implementation, necessary comments will also be generated every few lines (*e.g.*, "Check if lava is in the field of view in the previous step"). This approach not only allows Reward Designer to refer to the text-form thoughts during reward function initialization, but also assists subsequent Reward Critic in assessing the code's rationality, and helps Reward Designer to understand the current reward function's purpose when updating the reward function.

Scale Constraints. We impose a specific scale constraint for the reward function, where the LLM generates two sub-functions: dense and sparse. *Sparse* denotes rewards for

achieving the final goal or heavy penalties (like death), while *dense* represents dense intermediate signals during the task completion process. We preset their numerical values and only allow the LLM to determine their positivity or negativity, limiting *sparse* to $\{1, 0, -1\}$, and *dense* to $\{0.1, 0, -0.1\}$. They are then added together for the final reward. Therefore, the final reward values can be one value of $\{\pm 1.1, \pm 1.0, \pm 0.9, \pm 0.1, 0\}$. The final reward is calculated as $R = \text{sgn}(sparse) * 1 + \text{sgn}(dense) * 0.1$, where sgn denotes the sign function. This is to keep the reward within a reasonable range, allowing the LLM to focus on various scenarios that need to be considered in the reward function, rather than trivial tasks like adjusting the reward value.

3.2. Reward Critic

In practice, it is difficult for LLM to generate a relatively complete reward function in the beginning. There may be errors in understanding parameter formats and data types (**syntax errors**), failure to consider game-specific information, or misunderstanding of tasks (**semantic errors**), etc.

In order to eliminate above errors that are not easy to find, we design a LLM based Reward Critic to automatically review the designed reward function. In addition to checking for syntax errors, Reward Critic is also asked to check the quality of the reward function to further eliminate semantic errors. Specifically, we require Reward Critic to check whether the current code implementation matches its thoughts, whether it meets the reward function design requirements, and whether it takes game information into account. If the review fails, the Critic will provide a critique, and the Reward Designer will then modify the reward function based on the criterion and submit it for review again. The above process is repeated up to 3 times.

If an error occurs during the execution of the reward function in the process of interacting with the environment, the Python traceback of the error message will be fed back to Reward Designer for modification. These errors may include misunderstandings of input parameters, list index out of range, uninitialized keys in dictionaries, and other such issues. Some runtime errors only appear during the actual execution of the code.

3.3. Trajectory Analyzer

LLMs have the ability to understand environmental information and task instructions through in-context prompts to generate dense rewards. However, this zero-shot approach completely relies on LLM's understanding of the task and imagination of the problems it may face, and it is difficult to ensure the effectiveness of the designed reward. Take the the yellow highlighted part in Figure 1 as an example, in the initially designed reward function, Reward Designer does not consider the situation where the agent would encounter lava and be burned to death. Thus, in order to introduce em-
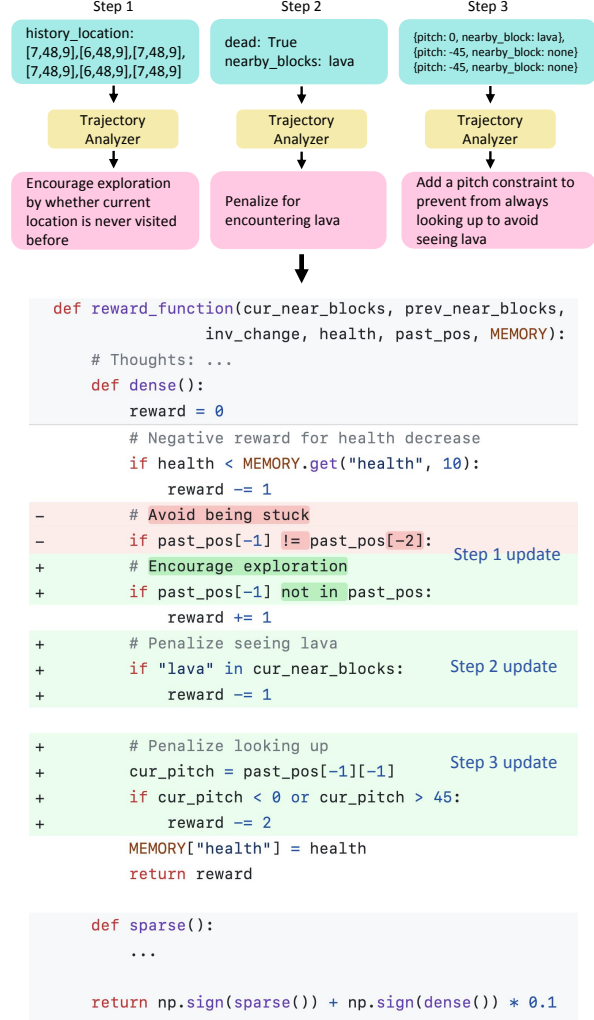

Figure 2. Example of updating the reward function. Trajectory Analyzer provides analysis for three scenarios at different steps, and then Reward Designer update the reward function based on the suggestions. We only display part of the trajectory data for brevity. **Step 1**: rewrite the code of encouraging exploration to avoid going back and forth. **Step 2**: add lava penalty to avoid falling into lava. **Step 3**: add pitch constraint to avoid constantly looking up to avoid lava.

pirical improvements to the designed dense reward, we propose to use LLMs, named as Trajectory Analyzer, to summarize the historical information of the interaction between the trained agent and the environment and use it to guide the revision of the reward function. The division of labor of Reward Designer and Trajectory Analyzer allows for independent operations of data analysis and reward function updates. Trajectory Analyzer does not need to know the details of the reward function, and Reward Designer does not need to process complex trajectory data.

Specifically, the current trained model is used to inter-

act with the environment and obtain K trajectories. Then, we truncate these trajectories and use a LLM to summarize the observations of the last consecutive L frames of each failed trajectory to automatically infer its possible failure reasons. Based on the analysis of the reasons for the failure, the LLM Trajectory Analyzer is asked to propose key points that Reward Designer needs to consider in the next round of reward function revision. For instance, failure scenarios where punishment is not considered, misalignment of dense reward and sparse reward causes the agent's behavior to deviate from the final goal, etc.

Figure 2 shows an example of multiple rounds of improving the reward function during the search for diamonds. In the first step, through analysis of the trajectory, Trajectory Analyzer finds that the agent would opportunistically find a shortcut to increase the reward, that is, move back and forth to deceive the reward function into thinking that the agent is moving actively. Therefore, the Reward Designer modifies the code snippet that encourages the agent to move, *i.e.* encourage the agent to appear in unvisited locations as much as possible. Although the initially designed reward function has taken into account the penalty for the loss of the agent's health, the agent still cannot effectively learn to avoid lava. When modifying the reward function in the second round, Trajectory Analyzer discovers through the failed trajectory that the agent may die from lava, so it is suggested that Reward Designer increase the penalty for encountering lava, as shown in the step 2 update in Figure 2. According to the interactive experience, Reward Designer explicitly punishes the continuous appearance of lava in the field of view. However, the excessive punishment of lava caused the agent to choose to turn its perspective upward or downward to avoid the appearance of lava in the visible range, making it impossible for the agent to continue effective exploration, which deviates from the ultimate goal. To this end, Reward Designer further constrain the agent's perspective in step 3, so that the lava disappeared from the agent's perspective by turning left/right while continuing to search for diamonds, which is the desired strategy. Figure 3(a) shows the successful trajectory of avoiding lava: The agent sees the lava after breaking the stone ahead using iron pickaxe, and then turn left to avoid the lava through the mining tunnel.

4. Experiment

4.1. Environment Setup

We mainly use the harvest mode in the MineDojo [13] environment to verify the model's ability to play Minecraft. The training pseudo code of Auto MC-Reward is shown in Algorithm 1. We set up the following challenging tasks for model performance comparison and ablation study:

- **Explore diamond ore** on the 11-th floor under-

Algorithm 1 Auto MC-Reward Training Pseudo Code

Require: Task (T), Inital Agent (A_0), Environment (Env), Max number of Critic reviews (N_{Critic})
Ensure: Final Agent (A_N), Final Reward (R_N)
  Summary = None
  Critique = None
  R_0 = None
  for $i = 1, \ldots, N$ **do**
    R_i = RewardDesigner(Summary, Critique, T, R_{i-1})
    for $j = 1, \ldots, N_{\text{Critic}}$ **do**
      Critique, Done = RewardCritic(R_i)
      if Done **then**
        break
      else
        R_i = RewardDesigner(Summary, Critique, T, R_i)
      end if
    end for
    A_i = TrainAgent(A_0, R_i, Env, T)
    Traj$_i$, Stat$_i$ = Eval(Env, A_i)
    Summary = TrajectoryAnalyzer(Traj$_i$, Stat$_i$)
    Critique = None
  end for

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ground: Initially, the agent is equipped with an iron pickaxe on the 11-th floor underground. When the diamond ore is within the visible range and the distance is less than 2 distance units, the task is deemed completed. The difficulty of the task lies in the fact that diamonds are very rare, lava frequently appears during exploration, leading to death, and the maximum number of steps is limited to 60,000. When steps exceed the limit, the trajectory is considered failed. Long-term exploration can demonstrate the advantages of dense rewards.

- **Approach tree on plains biome**: The task is considered successful if the tree is within the agent's visible range and the distance is less than 1 distance unit. The difficulty of the task lies in the fact that the trees are very sparse on plains, which is extremely detrimental to sparse reward functions. The maximum number of steps is limited to 2,000 steps.

- **Approach specific animal (*e.g.* cow, sheep) on plains biome**: The task is considered successful if the animal is within the agent's visible range and the distance is less than 2 distance unit. The difficulty of the task is that the animals are constantly moving. The maximum number of steps is limited to 2,000 steps.

- **Obtaining diamond**: The agent needs to complete the whole process of mining diamonds, including key behaviors such as finding and obtaining materials on the surface, crafting, digging down, going back to the ground, and mining stone/iron ore/diamond ore. The tech tree is shown in Figure 4.

(a) See the lava after breaking the stone ahead using iron pickaxe, and then turn left to avoid the lava through the mining tunnel.

(b) Find a herd of cows in the village, go forward and attack one of the cows with a stone pickaxe, and pick up the fallen beef and leather.

Figure 3. The trajectories of the new behaviors. (a) Avoid lava 🔥 when exploring for diamond ore 💎. (b) Attack cow 🐮 in plains villages.

4.2. Implementation Details

LLM Prompt. The components of the input prompts for Trajectory Analyzer include task description, game information, statistical metrics, and information on failed trajectories. Components of the input prompts for Reward Designer and Reward Critic includes task description, game information, input parameters, and reward function requirements and format. We use GPT-4 [35] for all the LLM components, and set temperature to 0.3.

- **Instruction**: Instructions on initializing, updating and handling execution error of reward function for Reward Designer, reviewing function for Reward Critic, and analyzing trajectory for Trajectory Analyzer.
- **Task description**: The objective, initial conditions, success criteria, and task flow. For example, for the explore diamond task, the objective is "to find and approach a diamond, achieving a high success rate while avoiding death." The initial condition is "agent at y level 11 with an iron pickaxe." The success criteria is "being less than 1 meter from the nearest diamond block", and the task flow is "horizontally explore to find a diamond, face it, and approach it". In the task description, we do not provide prior game strategy information (task challenges, DFS exploration strategies, or avoiding lava, etc.) to ensure the method's versatility.
- **Game information**: Game version, block names, field of view, action space, and units of measurement. Game information provides knowledge about the game's simulation environment, not game strategy.
- **Statistical metrics and information on failed trajectories**: success rates, and actions sequences, reward sequences, final inventory and nearby blocks of $K = 10$ failed trajectories. If a trajectory exceeds $L = 32$ steps, it is truncated to the last 32 steps.

- **Input parameters**: The nearest distance of each block type within the visible range in the current and previous steps, changes in inventory between adjacent steps, health points, and the agent's location in each past step. The memory is also provided as an input parameter for storing information to monitor changes across different steps. We provide explanation and examples of the parameters in the input prompt.
- **Reward function requirements and format**: We require the Designer to write a dense function and a sparse function, and consider only the sign of the two functions' return values, not the magnitude. The detail of the scale constraints is in Section 3.1.

Imitation Learning Details. When large labeled datasets do not exist, the canonical strategy for training capable agents is RL, which is inefficient and expensive to sample for hard-exploration problems [3, 4, 20], *e.g.* mining diamond in Minecraft. Therefore, in order to more efficiently explore the effectiveness of the LLM-based reward function design mechanism proposed in this paper, we pre-trained some foundation models through imitation learning as done by VPT [3]. Specifically, we use GITM [52] to continuously perform Diamond Mining task and record important observation data of each frame, such as RGB, action, inventory, GPS, compass, structured actions, etc. In the end, we collect about 11 million image data, totaling about 153 hours (the control frequency is 20 Hz) of game videos. Subsequently, we train these data through fully supervised learning by using Impala CNN [12] and Transformer [43] as backbone, and obtained several foundation models. The main differences between the foundation models are different biomes (forest and plains), temporal frames (16 and 128), and whether goal embedding is used. In subsequent experiments, these foundation models were used in two different purposes:

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Table 1. Comparison with other reward methods on three Minecraft tasks. Max steps for exploring tree 🌳 and cow 🐄 are set to 2000. †Sparse reward receives a low death rate because it is often stuck in the same place or move in a small area without encountering lava 🔥.

Method	Reward	Explore Diamond Ore ⛏ Underground				Approach Tree 🌳 on Plains		Approach Cow 🐄 on Plains	
		avg. dist. ↑	death (%) ↓	lava escape (%) ↑	succ. (%) ↑	avg. step ↓	succ. (%) ↑	avg. step ↓	succ. (%) ↑
Naive Handcraft	-	85.7	74.3	1.5	18.6	1993	2.1	1956	10.8
Imitation Learning	-	102.2	55.6	46.8	38.9	1988	2.5	1772	22.4
RL	Sparse	16.8	1.5†	0	0.5	1936	4.3	1854	12.6
RL	Dense (Curiosity)	102.6	55.1	46.0	39.3	1672	45.8	1477	13.7
RL	Dense (Self-Imitation)	104.0	54.8	47.2	39.7	1532	42.5	1280	23.5
RL	Dense (MineCLIP)	105.9	54.0	47.8	40.5	1022	65.6	1206	44.9
Ours	Dense (LLM)	**142.8**	**45.2**	**70.0**	**45.2**	**972**	**73.4**	**1134**	**56.3**

Table 2. Comparison with previous methods on success rates of obtaining diamond 💎. The observation listed in the table are only used in the inference phase. Auto MC-Reward achieves a remarkable success rate without exploiting unfair information (*i.e.* Lidar and Voxel) during inference.

Method	Controller	Observation	Diamond Succ. (%)
DreamerV3 [16]	RL	RGB, Status	0.01
DEPS [46]	IL	RGB, Status, Voxel	0.6
VPT [3]	IL + RL	RGB	20.0
GITM [52]	Handcraft	Lidar, Voxel, Status	55.0
Ours	IL (GITM-guided)	RGB, GPS	28.8
Ours	IL + RL	RGB, GPS	36.5

Table 3. Ablations on Reward Critic and Trajectory Analyzer for explore diamond ore ⛏ task. The first row corresponds to using the sparse reward from the original environment. †Sparse reward receives a low death rate because it is often stuck in the same place or move in a small area without encountering lava 🔥.

Designer	Critic	Analyzer	Avg. Dist. ↑	Death ↓	Lava Esc. ↑	Succ. ↑
			16.8	1.5†	0	0.5
✓			75.8	58.2	30.4	35.1
✓	✓		95.2	49.3	40.7	40.5
✓		✓	130.6	47.8	64.8	43.1
✓	✓	✓	**142.8**	**45.2**	**70.0**	**45.2**

- Give the RL model preliminary basic Minecraft gameplay capabilities, *e.g.* forward/back, turn left/right, attack, etc. For some tasks that have not been learned (*e.g.* approaching cows in Figure 3(b)) or not learned well (*e.g.* avoid lava in Figure 3(a), explore tree on plains) in imitation learning, RL algorithms can be studied more efficiently.
- In the Diamond Mining task, the diamond collection success rate, lava escape rate, death rate, etc. between the RL model and the imitation learning model are compared to demonstrate the superiority of the proposed method.

RL Training Details. We use proximal policy optimization (PPO) algorithm [38] with generalized advantage estimation (GAE) [37] to train our RL model. We use $\gamma = 0.99$ and $\lambda = 0.95$ for all of our experiments, and the total train-

ing frames is 256,000. To prevent catastrophically forgetting or overly aggressive policy update during RL training, we follow VPT [3] to apply an auxiliary Kullback-Leibler (KL) divergence loss between the RL model and the frozen pre-trained policy. We also normalize the reward based on the trajectory returns to constrain the gradient scales of different tasks. See Appendix for details.

4.3. Main Results

Baselines. We compare our Auto MC-Reward against the following methods:

- **Naive Handcraft**: The agent keeps moving (and mining for diamond exploration task) in one direction with a small probability of turning left/right.
- **Imitation Learning**: Our foundation model pre-trained with GITM-generated data, as introduced in Section 4.2.
- **RL with Sparse Reward**: Use only the reward from the original environment, *i.e.* only receives a reward when the success criteria is completed.
- **RL with Curiosity Dense Reward** [36]: Encourage the agent to discover and learn about parts of the environment that it has not encountered before.
- **RL with Self-Imitation Dense Reward** [34]: Encourage the agent to replicate its past actions that led to high rewards.
- **RL with MineCLIP [13] Dense Reward**: Use MineCLIP to calculate the dense reward based on the similarity between RGB frames and task objectives.

Results on Diamond Ore ⛏ Exploration Task. For the plain imitation learning model, fitting the training data makes it lack the awareness of avoiding lava, so it often dies in lava during the search for diamonds, and only has 38.9% success rate under the limit of 60,000 steps, as shown in Table 1. In contrast, our Auto MC-Reward makes the agent realize the importance of avoiding lava by continuously improving the dense reward function, and the final diamond success rate has increased to 45.2% with 70% lava escape success rate. Figure 3(a) demonstrates good awareness of avoiding lava. Based on the same reinforcement learning algorithm, the disadvantages of sparse reward functions in

Figure 4. The tech tree of obtaining diamond. The green squares are tasks to be optimized with Auto MC-Reward, *i.e.* obtaining log 🪵, cobblestone ⬛, iron ore ⬛ and diamond 💎.

Figure 5. Cumulative success rates for 4 key items of obtaining diamond on forest 🌲 and plains 🟩 biomes. In terms of diamond, the performance comparison between imitation learning and Auto MC-Reward in two biomes are: 28.8% vs. 36.5%, and 0% vs. 28.1%.

long-horizon tasks are undoubtedly revealed. By watching the videos of collected trajectories, we find that using sparse functions often leads to irreversible behavior, such as being unable to break the surrounding ores to move due to maintaining a head-up posture. Although a low death rate of 1.5% is achieved, the actual average moving distance is only 16.8, and the success rate is only 0.5%. Due to the similar scenes underground, MineCLIP cannot give differentiated rewards, so its performance is close to the initial imitation learning model. Other baselines, like curiosity and self-imitation dense reward, also have mediocre performance and the success rate has not been significantly improved.

Results on Tree 🪵 Approaching Task. Since trees are extremely sparse on the plain, the imitation learning model and the RL model with sparse reward cannot perform well, with only 2.5% and 4.3% success rates respectively, and their average action steps are close to the maximum limit. Table 1 shows that MineCLIP dense reward receives a success rate of 65.6% since it can provide positive reward when tree is visible. Curiosity and self-imitation methods also achieve better results than imitation learning. For Auto MC-Reward, Reward Designer uses a strategy of giving positive rewards for getting closer and deducting rewards for going away, so that the agent learns to slowly approach the target, ultimately achieving 73.4% success rate with only 972 average action steps.

Results on Cow 🐄 Approaching Task. The task of exploring for cows does not appear in the training data of imitation learning, so the zero-shot ability on this task is not ideal, with about 22.4% success rate and average steps close to the maximum limit. By checking the videos, we find most of the successful cases are due to good luck without intention to actively approach the target. The same experimental conclusion is also obtained in the experiment of sparse reward function. Similar to the Tree Approaching Task, the superior dense reward function design mechanism makes our agent 43.7% (56.3% vs. 12.6%) higher than sparse reward, as listed in Table 1. Another dense reward MineCLIP also shows strong performance in this task, but due to the need to calculate the similarity of images and texts at all times during training, the efficiency is unacceptable.
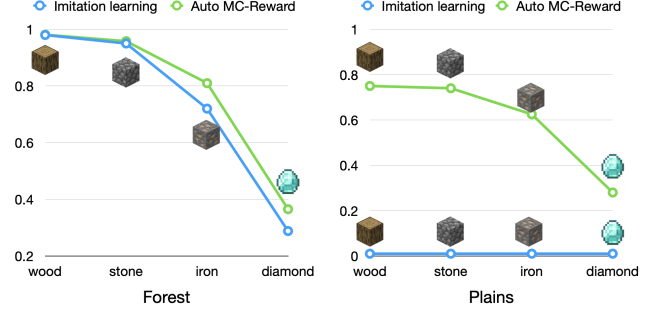
Results on Obtaining Diamond 💎. We verify the proposed method on a more difficult task, that is, the tech tree of collecting diamonds, as shown in Figure 4. As mentioned before, our foundation imitation learning model already has a certain ability from birth to diamond mining. We use the proposed method to optimize several key tasks in the process to increase the success rate of final diamond acquisition. The green parts in Figure 4 are the tasks that need to be optimized, *i.e.* obtaining log, cobblestone, iron ore and diamond. We conduct experiments on two biomes in Minecraft, and the cumulative success rate is shown in Figure 5. Specifically, the lower death rate allows our agent to have a higher success rate in mining iron ore and diamond, and ultimately achieves 36.5% success rate on forest biome, which is 7.7% higher than the imitation learning model. As for plains, the difficulty of obtaining log makes the imitation learning model unable to complete any tasks. Auto MC-Reward overcomes the difficulty of obtaining log, thus achieving a 28.1% success rate in obtaining diamonds. Table 2 provides a rough comparison of several different methods on the task of mining diamonds. We achieve a high success rate without exploiting unfair information (*i.e.* Lidar and Voxel) during the inference phase.

4.4. Ablation studies

Effectiveness of Reward Designer. The first row of Table 3 is an RL experiment with a sparse reward function. As mentioned before, it cannot explore diamonds normally. After adding Reward Designer, it regained the ability to explore under a dense reward function.

Effectiveness of Reward Critic. As listed in Table 3, the success rate of exploring diamonds has increased from 35.1% to 40.5% by adding Reward Critic, because it can reduce the syntax and semantic errors in the code, making the training process more effective and sufficient. For example, the Trajectory Analyzer concludes that the agent died in

lava and asks the Reward Designer to add relevant penalties. However, without being checked by Critic for semantic errors, it is possible that the added code snippet uses the word "magma" instead of the correct one "lava". This will result in insufficient learning of lava avoidance, which is reflected in a 2.1% (43.1% vs. 45.2%) success rate difference.

Effectiveness of Trajectory Analyzer. As observed in Table 3, Trajectory Analyzer is the key to helping the agent improve the success rate of completing tasks. It summarizes the reasons for failure to be fed into Reward Designer, allowing it to iteratively modify an appropriate dense reward function to guide the agent to overcome difficulties. In terms of Diamond Exploration Task, Trajectory Analyzer provides timely feedback on the potential risks of lava, which greatly improves the survival rate and moving distance, ultimately effectively improving the success rate from 40.5% to 45.2%.

5. Conclusion

We proposed Auto MC-Reward, an automated dense reward design framework for addressing challenges caused by sparse reward and complex environment of Minecraft. It addresses the issue of sparse rewards by leveraging LLMs to automatically generate dense reward functions, enhancing learning efficiency. The system consists of three key components: Reward Designer, Reward Critic, and Trajectory Analyzer, which are used for the design, verification and analysis of the reward function respectively. Auto MC-Reward's capabilities are validated through experiments, demonstrating a remarkable improvement in success rate and learning efficiency in complex tasks in Minecraft. Auto MC-Reward humbly contributes to more effective learning in complex tasks through its automated dense reward function design. We hope that our proposed method can pave the way for further research in reinforcement learning and its application to real-world problems.

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A. Experiments on Other Minecraft Tasks

A.1. Environment Setup

This section conducts experiments on more Minecraft tasks to verify the effectiveness of the proposed reward function design mechanism. The experiments mainly includes the approaching task of three animals including pig , sheep and chicken , as well as the attacking task of cow .

- **Approaching animals on plains biome.** The task is considered successful if the animal is within the agent's visible range and the distance is less than 2 distance unit. The difficulty of the task is that the animals are constantly moving and small (*e.g.* chicken). The maximum number of steps is limited to 2,000 steps.

- **Attacking cow on plains biome.** The task is considered successful if the agent successfully kills a cow and obtains beef or leather . The maximum number of steps is limited to 4,000 steps.

A.2. Results

Table I compares the performance between imitation learning model and ours. As the task of approaching for animals does not appear in the training data of imitation learning, our method achieves a significant improvement in success rate in fewer steps compared to imitation learning model's zero shot. In the more difficult task of attacking cow, our method also achieves clear advantages. By further checking the videos, we find most of the successful cases are due to good luck without intention to actively approach the target. In the supplementary materials, we have prepared several demo videos, in which we can clearly see that the agent trained by our method has a clear awareness of completing the corresponding tasks.

Table I. Compare imitation learning with our method on four Minecraft tasks.

Method	Approach Pig on Plains		Approach Sheep on Plains		Approach Chicken on Plains		Attack Cow on Plains	
	avg. step ↓	succ. (%) ↑	avg. step ↓	succ. (%) ↑	avg. step ↓	succ. (%) ↑	avg. step ↓	succ. (%) ↑
Imitation Learning	1664	25.0	1734	23.5	1496	36.4	3522	13.3
Ours	**830**	**67.3**	**1024**	**60.6**	**1391**	**54.5**	**3133**	**40.8**

B. Foundation Model Imitation Learning

B.1. Pretraining Data

When large labeled datasets do not exist, the canonical strategy for training capable agents is RL, which is inefficient and expensive to sample for hard-exploration problems [3, 4, 20], *e.g.* mining diamond in Minecraft. Therefore, in order to more efficiently explore the effectiveness of the LLM-based reward function design mechanism proposed in this paper, we pre-trained some foundation models through imitation learning as done by VPT [3]. Specifically, we use GITM [52] to continuously perform Diamond Mining task and record important observation data of each frame, such as RGB, action, inventory, compass (*e.g.* y_level), structured action (action plans), etc. The following is the format of the collected data:

```
{
  "action_plans": [
    {
      "name": "mine",
      "args": {
        "object": {"log": 1},
        "tool": None
      },
      "expectation": "Obtain 1 log"
    },
    ...
  ],

  "actions": [
    [0, 0, 0, 12, 12, 3, 0, 0],
```

```
      ...
    ],

    "y_level": [66, ...],

    "action_indices": [100, ...],

    "biomes": ["Forest", ...],

    "deaths": [0, ...],

    "visible_blocks": [
      [
         {"name": "wood", "nearest_distance": 0.71},
         ...
      ],
      ...
    ],

    "visible_entities": [
      [
         {"name": "cow", "nearest_distance": 4.57},
         ...
      ],
      ...
    ],

    "inventory": [{"log": 1}, ...],

    "task_names": ["Obtain 1 log", ...],

    "task_indices": [88, ...],
  }
```

Finally, we collect approximately 20.5/5.3 million image data on forest/plains biome, as listed in Table II. To reduce training costs, we only use 9 million and 2 million image data for training and validation on forest and plains biomes, respectively, totaling about 153 hours of game video (the control frequency is 20 Hz).

Table II. Detailed statistics of generated trajectories.

Item	Forest Biome				Plains Biome			
	trajectories	frames	max frames / traj.	min frames / traj.	trajectories	frames	max frames / traj.	min frames / traj.
log 🟫	14,790	5,209,246	13,806	8	3,254	2,425,602	14,373	10
planks 🟫	16,452	16,452	1	1	3,647	3,647	1	1
stick ╱	7,198	9,076	2	1	1,550	1,908	2	1
crafting table 🟫	3,452	3,452	1	1	837	837	1	1
wooden pickaxe ↗	2,972	408,056	2,263	72	685	97,529	2,328	106
cobblestone ⬛	3,047	1,704,098	13,107	180	681	341,737	6,681	184
stone pickaxe ↗	2,729	414,750	4,473	57	607	86,806	2,486	108
iron ore ⬛	2,177	6,498,252	14,833	200	461	1,394,251	12,783	235
furnace ⬛	1,879	280,604	7,912	86	362	55,101	2,885	28
iron ingot ⬭	1,632	497,513	7,334	17	281	91,585	4,916	254
iron pickaxe ↗	1,588	189,718	877	38	274	32,450	656	106
diamond 🔷	756	5,285,204	14,989	1,154	119	766,785	14,634	1,226
total	58,672	20,516,421	-	-	12,758	5,298,238	-	-

B.2. Action Space

We select 14 actions to train imitation learning for four tasks (obtain log/cobblestone/iron ore/diamond), as shown in Table III.

Table III. Action space used in our method.

Index	Action Name	Action Box	Index	Action Name	Action Box
0	no_op	[0, 0, 0, 12, 12, 0, 0, 0]	7	jump	[0, 0, 1, 12, 12, 0, 0, 0]
1	turn_up	[0, 0, 0, 11, 12, 0, 0, 0]	8	back	[2, 0, 0, 12, 12, 0, 0, 0]
2	turn_down	[0, 0, 0, 13, 12, 0, 0, 0]	9	move_left	[0, 1, 0, 12, 12, 0, 0, 0]
3	turn_left	[0, 0, 0, 12, 11, 0, 0, 0]	10	move_right	[0, 2, 0, 12, 12, 0, 0, 0]
4	turn_right	[0, 0, 0, 12, 13, 0, 0, 0]	11	attack	[0, 0, 0, 12, 12, 3, 0, 0]
5	forward	[1, 0, 0, 12, 12, 0, 0, 0]	12	equip	[0, 0, 0, 12, 12, 5, 0, 0]
6	forward_jump	[1, 0, 1, 12, 12, 0, 0, 0]	13	jump_place	[0, 0, 1, 12, 12, 6, 0, 0]

B.3. Training Details

Subsequently, we conduct fully supervised training on the four main tasks of the Diamond mining Task, *i.e.* log, cobblestone, iron ore, diamond, by using Impala CNN [12] and Transformer [43] as backbone, and obtained several foundation models. The main differences between the foundation models are different biomes (forest and plains), temporal frames (16 and 128), and whether goal and y_level embeddings are used as conditions. We use 32 A800 GPUs for foundation model training, and initialize the network using the foundation model of VPT to speed up the training of imitation learning. The hyperparameters are listed in Table IV.

Table IV. Hyperparameters for imitation learning.

Hyperparameter	Value
Learning rate	1e-4
Batch size	128
Epochs	25
Optimizer	Adam

The obtained foundation models, especially the goal-conditioned one, already have satisfactory basic behavioral capabilities. Based on these models, this paper uses the proposed methods to further improve existing behaviors (*e.g.* avoid lava while exploring diamond) and complete new tasks (*e.g.* approaching / killing animals).

C. Reinforcement Learning Training

We use proximal policy optimization (PPO) algorithm [38] with generalized advantage estimation (GAE) [37] implemented in TorchRL [5] library to train our RL model. The main hyperparameters used for RL training are listed in Table V.

In addition to the above hyperparameters, several training techniques are applied to all of our experiments:

- We follow VPT [3] to apply an auxiliary Kullback-Leibler (KL) divergence loss between the RL model and the frozen pretrained policy to prevent catastrophically forgetting or overly aggressive policy update during RL training, *e.g.*, maintaining the ability to dig horizontal tunnels. This loss is defined as:

$$L_{kl} = \alpha \mathrm{KL}(\pi_{pt}, \pi_\theta) \tag{1}$$

where π_θ is the the policy being trained, π_{pt} is the frozen pretrained policy, $\mathrm{KL}(\pi_{pt}, \pi_\theta)$ is the Kullback-Leibler divergence between the policy being trained and the pretrained policy, and α is the loss weight that is set to 0.125 by default.

Table V. Hyperparameters for reinforcement learning.

Hyperparameter	Value
Learning rate	5e-5
Total training frames	256,000
Batches per iteration	64
Discount factor (γ)	0.99
GAE λ	0.95
Value pre-training iteration	2
PPO clip	0.1
Entropy loss weight	0.1
Critic loss type	L_2
Critic coefficient	1
Optimizer	Adam

- We also normalize the reward based on the trajectory returns to constrain the return scales of different tasks. The formula is as follows:

$$R' = \text{mean}(\text{abs}(R))$$
$$R'_{cur} = \beta R'_{cur} + (1 - \beta)R'_{pre}$$
$$r_{norm} = \frac{r}{\max(R'_{cur}, 1)}$$

(2)

where r and R are reward and trajectory returns. β is a momentum parameter, set as 0.7 by default.

D. Full Text Prompts

We provide all the LLM input prompts of our method in this section.

D.1. Task Description

The task description contains task objective, initial status, success criteria and procedure of each task. It describe basic information of a task without prior knowledge like game strategies.

Exploring Diamond Ore

Task description

- Objective: Find and approach diamond with higher success rate and avoid death.

- Initial Status:
  1. The agent is under ground at y level 11, the most common level to find diamonds.
  2. The agent already has an iron pickaxe.
- Success criteria: The distance to the nearest diamond block is less than 2 meters.

- Procedure: Explore horizontally to find a diamond, face it and approach it.

Approaching a Tree on Plains

Task description

- Objective: Find and approach wood in the plains biome.

- Initial Status: The agent is on the ground.

- Success Criteria: The distance to the nearest wood block is less than 1 meters.

- Procedure: Find a wood, face it and approach it.

- Additional Information: Wood is sparse in plains biome. The agent may need to walk a long distance to find and approach a wood.

Approaching a Cow 🐮 on Plains 🏞️

Task description

- Objective: Find and approach cow in the plains biome.

- Initial Status: The agent is on the ground.

- Success Criteria: The distance to the nearest cow is less than 2 meters.

- Procedure: Find a cow, face it and approach it.

Attacking a Cow ⚔️🐮 on Plains 🏞️

Task description

- Objective: Find, approach and kill cow in the plains biome.

- Initial Status: The agent is on the ground.

- Success Criteria: The agent successfully kills a cow.

- Procedure: Find a cow, face it, approach it and kill it.

D.2. Reward Designer

Prompts for Reward Designer include prompts for initializing reward function, updating reward function, and handling critic failure and execution error.

Prompt for Initializing Reward Function

You are now a proficient Minecraft player. You should help me write proper reward functions to train a Minecraft agent with reinforcement learning to complete the described task.

`{task_description}`

Input parameters of the reward function

- current_nearest_blocks: nearby block types and nearest distance of each block type at the **current step**. It is a dictionary, consisting of the names, relative distances with the agent, and relative angles (yaw and pitch) with the agent, in the form of: {NAME_1: (DIST_1, YAW_1, PITCH_1), NAME_2: (DIST_2, YAW_2, PITCH_2)}. For example, {"wood": (24.7, 1.48, -1.57), "cobblestone": (1.3, -0.17, 1.05), "iron_ore": (4.5, 0.61, -0.17)}. If a certrain block type does not exist in the field of view, it is not present in the dictionary. The yaw and pitch here is relative to the agent's front, i.e., pitch = 0 and yaw = 0 is the front of the agent.

- previou_nearest_blocks: nearby block types and nearest distance of each block type at the **previous step**, with the same format as the current_nearest_blocks.

- inventory_change: the change of the agent's inventory from the previous step to current step, in the form of a dictionary: {NAME_1: CHANGE_NUM_1, NAME_2: CHANGE_NUM_2}. Positive values mean increase and negative values mean decrease. For example, {"wood": 2, "dirt": 3, "stone_pickaxe": -1}.

- health: an integer value in range 0 to 10 indicating the health level of the agent. 0 means death and 10 means full health.

- past_agent_positions: the history of location of agent, in the form of a list: [[x1, y1, z1, yaw1, pitch1], [x2, y2, z2, yaw2, pitch2], ...]. The yaw and pitch here are relative to the agent's initial forward direction, i.e., pitch = 0 and yaw = 0 is the front of the agent when it was born. The length of the list is the number of steps the agent has taken. The last element of the list is the current location of the agent.

- GLOBAL_DATA: a global variable. It is initialized as a dictionary. You can save necessary information between different steps with it.

General game information

- The version of Minecraft is 1.11.

- Common block names : dirt, cobblestone, iron, diamond, wood, coal, water, air, lava, leaves, ... Collected item names are the same.

- FOV is set to -35 to 35 degrees for yaw and -30 to 30 degrees for pitch. The max visible distance of blocks is 64.

- Length of each block is 1 meter.

- The y coordinate of the agent is the agent's height. The larger the y, the higher the agent. The ground level is around y = 63, but is not fixed.

- At each step, the agent selects one operation in is action space. The action space includes doing nothing (i.e. staying still), moving forward and backward, jumping and attacking. The action space also includes turning left, right, up and down.

- The attack range is 2 meters in front of the agent. The agent can move 0.2 meters in each step. The agent can turn 15 degrees in each step. Typically, the agent needs to stay still and attack for **60 successive steps** to break a block.

- The hunger value is always at the max level.

Reward function requirements

- You should write a dense reward function `dense` and a sparse reward function `sparse`. The sparse reward indicates achieving the goal or receiving heavy punishment. The dense reward provides intermediate signal to guide the agent in the process of achieving the goal. The magnitude of the return value does not matter, but the sign (positive or negative) is important. The final reward will be `np.sign(sparse(...)) * 1 + np.sign(dense(...)) * 0.1`.

Output Requirements

- The reward function should be written in Python 3.9.

- Output the code block only. **Do not output anything else outside the code block**.

- You should include **sufficient comments** in your reward function to explain your thoughts, the objective and **implementation details**. The implementation can be specified to a specific line of code.

- If you need to import packages (e.g. math, numpy) or define helper functions, define them at the beginning of the function. Do not use unimported packages and undefined functions.

Output format

Strictly follow the following format. **Do not output anything else outside the code block**.

```python
def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    # Thoughts:
    # ...
    # (import packages and define helper functions)
    import numpy as np
    ...
    def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        ...
    def sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        ...
    dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
    sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
    return np.sign(sparse_reward) * 1 + np.sign(dense_reward) * 0.1
    ...
```

Now write a reward function. Then in each iteration, I will use the reward function to train an RL agent, and test it in the

environment. I will give you possible reasons of the failure found during the testing, and you should modify the reward function accordingly.

Prompt for Updating Reward Function

You are now a proficient Minecraft player. I now have a reward function to train a Minecraft agent with reinforcement learning to complete the described task. The reward function is used to train the reinforcement learning agent for several times. I will provide you the analysis of failure and inefficiency and suggestions. You should help me modify the reward function.

{task_description}

Input parameters of the reward function

- current_nearest_blocks: nearby block types and nearest distance of each block type at the **current step**. It is a dictionary, consisting of the names, relative distances with the agent, and relative angles (yaw and pitch) with the agent, in the form of: {NAME_1: (DIST_1, YAW_1, PITCH_1), NAME_2: (DIST_2, YAW_2, PITCH_2)}. For example, {"wood": (24.7, 1.48, -1.57), "cobblestone": (1.3, -0.17, 1.05), "iron_ore": (4.5, 0.61, -0.17)}. If a certrain block type does not exist in the field of view, it is not present in the dictionary. The yaw and pitch here is relative to the agent's front, i.e., pitch = 0 and yaw = 0 is the front of the agent.

- previou_nearest_blocks: nearby block types and nearest distance of each block type at the **previous step**, with the same format as the current_nearest_blocks.

- inventory_change: the change of the agent's inventory from the previous step to current step, in the form of a dictionary: {NAME_1: CHANGE_NUM_1, NAME_2: CHANGE_NUM_2}. Positive values mean increase and negative values mean decrease. For example, {"wood": 2, "dirt": 3, "stone_pickaxe": -1}.

- health: an integer value in range 0 to 10 indicating the health level of the agent. 0 means death and 10 means full health.

- past_agent_positions: the history of location of agent, in the form of a list: [[x1, y1, z1, yaw1, pitch1], [x2, y2, z2, yaw2, pitch2], ...]. The yaw and pitch here are relative to the agent's initial forward direction, i.e., pitch = 0 and yaw = 0 is the front of the agent when it was born. The length of the list is the number of steps the agent has taken. The last element of the list is the current location of the agent.

- GLOBAL_DATA: a global variable. It is initialized as a dictionary. You can save necessary information between different steps with it.

General game information

- The version of Minecraft is 1.11.

- Common block names : dirt, cobblestone, iron, diamond, wood, coal, water, air, lava, leaves, ... Collected item names are the same.

- FOV is set to -35 to 35 degrees for yaw and -30 to 30 degrees for pitch. The max visible distance of blocks is 64.

- Length of each block is 1 meter.

- The y coordinate of the agent is the agent's height. The larger the y, the higher the agent. The ground level is around y = 63, but is not fixed.

- At each step, the agent selects one operation in is action space. The action space includes doing nothing (i.e. staying still), moving forward and backward, jumping and attacking. The action space also includes turning left, right, up and down.

- The attack range is 2 meters in front of the agent. The agent can move 0.2 meters in each step. The agent can turn 15 degrees in each step. Typically, the agent needs to stay still and attack for **60 successive steps** to break a block.

- The hunger value is always at the max level.

Reward function requirements

- You should write a dense reward function `dense`and a sparse reward function `sparse`. The sparse reward indicates achieving the goal or receiving heavy punishment. The dense reward provides intermediate signal to guide the agent in the process of achieving the goal. The magnitude of the return value does not matter, but the sign (positive or negative) is important. The final reward will be `np.sign(sparse(...)) * 1 + np.sign(dense(...)) * 0.1`.

Current reward function

{current_reward_function}

Reward function test result

The reward function is used to train the reinforcement learning agent for several times. Here is some analysis of failure and inefficiency and suggestions:
```

{analysis}
```

Requirements

Please consider the analysis and suggestions above and modify the reward function.

1. You can both modify the current lines and add new lines.

2. If necessary, you can write a **totally different** reward function than the current one.

3. Consider modifing the reward and penalty values in the current reward function to balance them.

4. In the first part of the reward function, you should provide your thoughts of modifying the reward function. **The thoughts should be concise.**

Output format

Strictly follow the following format. **Do not output anything else outside the code block**.

def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
  # Thoughts:
  # ...
  # (import packages and define helper functions)
  import numpy as np
  ...
  def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    ...
  def sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    ...
  dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
  sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
  return np.sign(sparse_reward) * 1 + np.sign(dense_reward) * 0.1
  ...

Prompt for Critic Failure

The reward function fails to pass the verification. The reasoning is:
```

{reasoning}
```

The critique is:
```

{critique}
```

Requirements

Please consider the reasoning and critique, and modify the reward function.

1. If necessary, you can write a totally different reward function than the current one.

2. In the first part of the reward function, you should provide your thoughts of modifying the reward function. The thoughts should not directly copy the given reasoning or critique. **The thoughts should be concise.**

Reward function requirements

- You should write a dense reward function `dense` and a sparse reward function `sparse`. The sparse reward indicates achieving the goal or receiving heavy punishment. The dense reward provides intermediate signal to guide the agent in the process of achieving the goal. The magnitude of the return value does not matter, but the sign (positive or negative) is important. The final reward will be `np.sign(sparse(...)) * 1 + np.sign(dense(...)) * 0.1`.

Output format

Strictly follow the following format. **Do not output anything else outside the code block**.

```
def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    # Thoughts:
    # ...
    # (import packages and define helper functions)
    import numpy as np
    ...
    def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        ...
    def sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        ...
    dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
    sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
    return np.sign(sparse_reward) * 1 + np.sign(dense_reward) * 0.1
    ...
```

Prompt for Code Execution Error

You are now a proficient Minecraft player. I now have a reward function to train a Minecraft agent with reinforcement learning to complete the described task. The reward function now encounters an execution error. I will provide you the execution error and the reward function. You should help me modify the reward function.

`{task_description}`

Input parameters of the reward function

- current_nearest_blocks: nearby block types and nearest distance of each block type at the **current step**. It is a dictionary, consisting of the names, relative distances with the agent, and relative angles (yaw and pitch) with the agent, in the form of: {NAME_1: (DIST_1, YAW_1, PITCH_1), NAME_2: (DIST_2, YAW_2, PITCH_2)}. For example, {"wood": (24.7, 1.48, -1.57), "cobblestone": (1.3, -0.17, 1.05), "iron_ore": (4.5, 0.61, -0.17)}. If a certrain block type does not exist in the field of view, it is not present in the dictionary. The yaw and pitch here is relative to the agent's front, i.e., pitch = 0 and yaw = 0 is the front of the agent.

- previou_nearest_blocks: nearby block types and nearest distance of each block type at the **previous step**, with the same format as the current_nearest_blocks.

- inventory_change: the change of the agent's inventory from the previous step to current step, in the form of a dictionary: {NAME_1: CHANGE_NUM_1, NAME_2: CHANGE_NUM_2}. Positive values mean increase and negative values mean decrease. For example, {"wood": 2, "dirt": 3, "stone_pickaxe": -1}.

- health: an integer value in range 0 to 10 indicating the health level of the agent. 0 means death and 10 means full health.

- past_agent_positions: the history of location of agent, in the form of a list: [[x1, y1, z1, yaw1, pitch1], [x2, y2, z2, yaw2, pitch2], ...]. The yaw and pitch here are relative to the agent's initial forward direction, i.e., pitch = 0 and yaw = 0 is the front of the agent when it was born. The length of the list is the number of steps the agent has taken. The last element of the list is the current location of the agent.

- GLOBAL_DATA: a global variable. It is initialized as a dictionary. You can save necessary information between different steps with it.

General game information

- The version of Minecraft is 1.11.

- Common block names : dirt, cobblestone, iron, diamond, wood, coal, water, air, lava, leaves, ... Collected item names are the same.

- FOV is set to -35 to 35 degrees for yaw and -30 to 30 degrees for pitch. The max visible distance of blocks is 64.

- Length of each block is 1 meter.

- The y coordinate of the agent is the agent's height. The larger the y, the higher the agent. The ground level is around y = 63, but is not fixed.

- At each step, the agent selects one operation in is action space. The action space includes doing nothing (i.e. staying still), moving forward and backward, jumping and attacking. The action space also includes turning left, right, up and down.

- The attack range is 2 meters in front of the agent. The agent can move 0.2 meters in each step. The agent can turn 15 degrees in each step. Typically, the agent needs to stay still and attack for **60 successive steps** to break a block.

- The hunger value is always at the max level.

Reward function requirements

- You should write a dense reward function `dense` and a sparse reward function `sparse`. The sparse reward indicates achieving the goal or receiving heavy punishment. The dense reward provides intermediate signal to guide the agent in the process of achieving the goal. The magnitude of the return value does not matter, but the sign (positive or negative) is important. The final reward will be `np.sign(sparse(...)) * 1 + np.sign(dense(...)) * 0.1`.

Current reward function

{current_reward_function}

Execution error traceback

```

{execution_error}

```

Requirements

Please consider the reason of error and modify the reward function.

In the first part of the reward function, you should write your analysis of the error in comments, and provide your thoughts of modifying the reward function. **The analysis and thoughts should be concise.**

Output format

Strictly follow the following format. **Do not output anything else outside the code block**.

```
def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    # Thoughts:
    # ...
    # (import packages and define helper functions)
    import numpy as np
    ...
    def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        ...
    def sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
```

```
GLOBAL_DATA):
    ...
    dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
GLOBAL_DATA)
    sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
GLOBAL_DATA)
    return np.sign(sparse_reward) * 1 + np.sign(dense_reward) * 0.1
    ...
```

D.3. Reward Critic

The prompt for Reward Critic judges whether the current reward function meets the requirements, and provides critique when the judgement fails.

You are now a proficient Minecraft player. I will give you a reward function written in Python, which is used to train an RL agent to play Minecraft.

You should help me to evaluate whether the reward function has met the requirements.

{task_description}

Input parameters of the reward function

- current_nearest_blocks: nearby block types and nearest distance of each block type at the **current step**. It is a dictionary, consisting of the names, relative distances with the agent, and relative angles (yaw and pitch) with the agent, in the form of: {NAME_1: (DIST_1, YAW_1, PITCH_1), NAME_2: (DIST_2, YAW_2, PITCH_2)}. For example, {"wood": (24.7, 1.48, -1.57), "cobblestone": (1.3, -0.17, 1.05), "iron_ore": (4.5, 0.61, -0.17)}. If a certrain block type does not exist in the field of view, it is not present in the dictionary. The yaw and pitch here is relative to the agent's front, i.e., pitch = 0 and yaw = 0 is the front of the agent.

- previou_nearest_blocks: nearby block types and nearest distance of each block type at the **previous step**, with the same format as the current_nearest_blocks.

- inventory_change: the change of the agent's inventory from the previous step to current step, in the form of a dictionary: {NAME_1: CHANGE_NUM_1, NAME_2: CHANGE_NUM_2}. Positive values mean increase and negative values mean decrease. For example, {"wood": 2, "dirt": 3, "stone_pickaxe": -1}.

- health: an integer value in range 0 to 10 indicating the health level of the agent. 0 means death and 10 means full health.

- past_agent_positions: the history of location of agent, in the form of a list: [[x1, y1, z1, yaw1, pitch1], [x2, y2, z2, yaw2, pitch2], ...]. The yaw and pitch here are relative to the agent's initial forward direction, i.e., pitch = 0 and yaw = 0 is the front of the agent when it was born. The length of the list is the number of steps the agent has taken. The last element of the list is the current location of the agent.

- GLOBAL_DATA: a global variable. It is initialized as a dictionary. You can save necessary information between different steps with it.

General game information

- The version of Minecraft is 1.11.

- Common block names : dirt, cobblestone, iron, diamond, wood, coal, water, air, lava, leaves, ... Collected item names are the same.

- FOV is set to -35 to 35 degrees for yaw and -30 to 30 degrees for pitch. The max visible distance of blocks is 64.

- Length of each block is 1 meter.

- The y coordinate of the agent is the agent's height. The larger the y, the higher the agent. The ground level is around y = 63, but is not fixed.

- At each step, the agent selects one operation in is action space. The action space includes doing nothing (i.e. staying still), moving forward and backward, jumping and attacking. The action space also includes turning left, right, up and down.

- The attack range is 2 meters in front of the agent. The agent can move 0.2 meters in each step. The agent can turn 15 degrees in each step. Typically, the agent needs to stay still and attack for **60 successive steps** to break a block.

- The hunger value is always at the max level.

Reward function requirements

- You should write a dense reward function `dense` and a sparse reward function `sparse`. The sparse reward indicates achieving the goal or receiving heavy punishment. The dense reward provides intermediate signal to guide the agent in the process of achieving the goal. The magnitude of the return value does not matter, but the sign (positive or negative) is important. The final reward will be `np.sign(sparse(...)) * 1 + np.sign(dense(...)) * 0.1`.

Requirements

1. You should check whether the reward function meets the **reward function requirements** above.

2. Your judgement should consider whether the comments and the detailed implementation code are consistent. You can judge whether a line is correct by its comment, but do only rely on the comments.

3. You should also check the format of the reward function. It should be like:

def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
  # Thoughts:
  # ...
  # (import packages and define helper functions)
  import numpy as np
  ...
  def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    ...
  def sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    ...
  dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
  sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
  return np.sign(sparse_reward) * 1 + np.sign(dense_reward) * 0.1
  ...

4. Consider the **Information about the game state** above.

5. **You don't need to check whether the reward function meets the task description**.

6. You should first provide a reasoning and decision. If the reward function fails, provide a critique to help to improve the reward function.

Output format

You should only respond in JSON format as described below:

{
  "reasoning": "reasoning",
  "success": boolean,
  "critique": critique,
}

Ensure the response can be parsed by Python `json.loads`, e.g. no trailing commas, no single quotes, etc. Do not output anything else like explanations.

Reward function to be evaluated

```
{reward_function}
```

D.4. Trajectory Analyzer

The prompt for Trajectory Analyzer analyzes the trajectory information and statistics, and provides possible reasons of failure and suggestions on game strategy.

You are now a proficient Minecraft player. I have trained an RL agent and tested for several times in the Minecraft game environment.

I will give you the information of the failed test results, i.e. trajectories of actions, rewards and observations. You should help me write proper analysis of possible reasons of failure and inefficiency, and your suggestion on the game strategy.

{task_description}

General game information

- The version of Minecraft is 1.11.

- Common block names : dirt, cobblestone, iron, diamond, wood, coal, water, air, lava, leaves, ... Collected item names are the same.

- FOV is set to -35 to 35 degrees for yaw and -30 to 30 degrees for pitch. The max visible distance of blocks is 64.

- Length of each block is 1 meter.

- The y coordinate of the agent is the agent's height. The larger the y, the higher the agent. The ground level is around y = 63, but is not fixed.

- At each step, the agent selects one operation in is action space. The action space includes doing nothing (i.e. staying still), moving forward and backward, jumping and attacking. The action space also includes turning left, right, up and down.

- The attack range is 2 meters in front of the agent. The agent can move 0.2 meters in each step. The agent can turn 15 degrees in each step. Typically, the agent needs to stay still and attack for **60 successive steps** to break a block.

- The hunger value is always at the max level.

Input format

Failed trajectories

The failed trajectories are shown as a list, where each entry is a dictionary representing a trajectory. Note that **only the failed cases are provided.**

The each item of "history" is a list representing statistics of each single step. When the history is too long, it will be truncated to the last 32 steps, indicated by the value of "truncated".

"dead" indicates whether the agent has died.

The format is:

```
[
  {
    "history": {
      "rewards": [reward1, ...],
      "actions": [action1, action2, ...],
      "locations": [[x1, y1, z1, pitch1, yaw1], ...],
      "inventory_change": {item1: delta_num1, ...},
      "truncated": True or False,
    },
    "final_health": health,
    "final_inventory": {item1: num1, ...},
    "final_nearest_blocks": {block_name1: nearest_distance1, block_name2: nearest_distance2, ...},
    "block_under_foot": block_name,
    "dead": True or False,
  },
  ...
]
```

where "final_health" is in range 0 and 10. "block_under_foot" is the block right under the agent.

Statistics

The statistics is a dictionary of all the test results, including **both successful and failed trajectories**.

The format is:

```
{
   "success_rate" : success_rate,
}
```

Requirements

Please write proper analysis of possible reasons of failure and inefficiency, and your suggestion on the game strategy. You should not not be limited to the task description above, but also come up with other failure cases based on the test results.

The analysis and suggestion should be concise.

Test results

Failed trajectories

{trajectories}

Statistics

{statistics}

E. Examples of LLM-Designed Reward Functions

We provide reward function examples for four tasks. For the attacking cow task, we add two extra input parameters *damage_dealt* and *kill_entity*, which records the amount of damage the agent caused and the amounts of each entity the agent killed, respectively.

Algorithm I Reward Function Example of Exploring Diamond Ore 🧊

```python
def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions
    , GLOBAL_DATA):
    """
    Thoughts:
    In order to make the agent approach the diamond, we need to give positive rewards for actions that
    make the agent get closer to the diamond and negative rewards for actions that make the agent get further from
    the diamond.
    We also need to give a negative reward if the agent's health decreases to encourage the agent to avoid
    dangerous situations.
    The dense reward function will be based on the distance to the diamond and health.
    The sparse reward function will give a large positive reward when the agent reaches the diamond and a large
    negative reward when the agent dies.
    In addition, we should implement a threat detection mechanism to avoid unnecessary deaths.
    """
    import numpy as np

    def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
    GLOBAL_DATA):
        # Initialize reward
        reward = 0

        # If the agent is closer to diamond than before, give a positive reward
        if "diamond" in current_nearest_blocks and "diamond" in previous_nearest_blocks:
            if current_nearest_blocks["diamond"][0] < previous_nearest_blocks["diamond"][0]:
                reward += 1
            elif current_nearest_blocks["diamond"][0] > previous_nearest_blocks["diamond"][0]:
                reward -= 1

        # If the agent is close to lava, give a negative reward
        if "lava" in current_nearest_blocks:
            reward -= 1

        # If the agent is not in pitch range 0 to 45, give a negative reward
        cur_pitch = past_agent_positions[-1][-1]
        if cur_pitch < 0 or cur_pitch > 45:
            reward -= 2

        # If the agent's health decreases, give a negative reward
        if "health" in GLOBAL_DATA:
            if health < GLOBAL_DATA["health"]:
                reward -= 1
        GLOBAL_DATA["health"] = health

        return reward

    def sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
    GLOBAL_DATA):
        # Initialize reward
        reward = 0

        # If the agent reaches the diamond, give a large positive reward
        if "diamond" in current_nearest_blocks and current_nearest_blocks["diamond"][0] < 2:
            reward += 100

        # If the agent dies, give a large negative reward
        if health == 0:
            reward -= 100

        return reward

    dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health,
    past_agent_positions, GLOBAL_DATA)
    sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health,
    past_agent_positions, GLOBAL_DATA)

    return np.sign(sparse_reward) * 1 + np.sign(dense_reward) * 0.1
```

Algorithm II Reward Function Example of Approaching a Tree 🪵 on Plains 🏞.

```python
def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions
    , GLOBAL_DATA):
    # Thoughts:
    # Objective: The agent should approach the nearest wood block in the plains biome.
    # We want to encourage the agent to:
    # - Make progress towards wood
    # - Keep health high
    # - Avoid circling around or staying still
    # We use a dense reward to encourage the above behaviors, and a sparse reward to give a big bonus when the
     agent achieves the objective.
    import numpy as np
    import math

    # Helper function to calculate the Euclidean distance between two points
    def calculate_distance(point1, point2):
        return math.sqrt(sum([(a - b) ** 2 for a, b in zip(point1, point2)]))

    def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
     GLOBAL_DATA):
        reward = 0

        # Encourage the agent to approach wood
        if "wood" in current_nearest_blocks:
            current_distance = current_nearest_blocks["wood"][0]
            if "wood" in previous_nearest_blocks:
                previous_distance = previous_nearest_blocks["wood"][0]
                # Encourage the agent to decrease the distance to the nearest wood
                if current_distance < previous_distance:
                    reward += 1
                # Discourage the agent to increase the distance to the nearest wood
                else:
                    reward -= 1
            # Encourage the agent to find wood
            else:
                reward += 1

        # Encourage the agent to keep health high
        if health <= 3:
            reward -= 1

        # Discourage the agent from circling around or staying still
        if len(past_agent_positions) > 1:
            current_position = past_agent_positions[-1][:3]
            previous_position = past_agent_positions[-2][:3]
            # Encourage the agent to move
            if calculate_distance(current_position, previous_position) < 0.1:
                reward -= 1

        return reward

    def sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
     GLOBAL_DATA):
        reward = 0

        # Give a big bonus when the agent achieves the objective
        if "wood" in current_nearest_blocks and current_nearest_blocks["wood"][0] < 1:
            reward += 10

        return reward

    dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health,
     past_agent_positions, GLOBAL_DATA)
    sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health,
     past_agent_positions, GLOBAL_DATA)

    return np.sign(sparse_reward) * 1 + np.sign(dense_reward) * 0.1
```

Algorithm III Reward Function Example of Approaching a Cow 🐄 on Plains 🏞️

```python
def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions
    , GLOBAL_DATA):
    """
    Thoughts:
    - The agent needs to find a cow and approach it. So, the primary factor affecting the reward is the distance to
      the nearest cow.
    - The agent should avoid getting hurt (losing health).
    - We do not need to consider inventory change in this task.
    - We need to encourage the agent to keep exploring, so we also consider the agent's movement.
    """

    import numpy as np

    # Helper function to calculate the Euclidean distance between two positions
    def calculate_distance(pos1, pos2):
        return np.sqrt((pos1[0] - pos2[0]) ** 2 + (pos1[1] - pos2[1]) ** 2 + (pos1[2] - pos2[2]) ** 2)

    def dense(current_nearest_blocks, previous_nearest_blocks, health, past_agent_positions):
        # Reward for approaching the cow
        cow_reward = 0
        if "cow" in current_nearest_blocks:
            if "cow" in previous_nearest_blocks:
                # If the agent is getting closer to the cow, give a positive reward
                if current_nearest_blocks["cow"][0] < previous_nearest_blocks["cow"][0]:
                    cow_reward = 1
                # If the agent is getting farther from the cow, give a negative reward
                elif current_nearest_blocks["cow"][0] > previous_nearest_blocks["cow"][0]:
                    cow_reward = -1

        # Reward for moving (exploring)
        move_reward = 0
        if len(past_agent_positions) > 1:
            # If the agent is moving, give a positive reward
            if calculate_distance(past_agent_positions[-1], past_agent_positions[-2]) > 0:
                move_reward = 1
            # If the agent is not moving, give a negative reward
            else:
                move_reward = -1

        return cow_reward + move_reward

    def sparse(current_nearest_blocks, health):
        # If the agent finds a cow and approaches it successfully, give a large positive reward
        if "cow" in current_nearest_blocks and current_nearest_blocks["cow"][0] < 2:
            return 100
        # If the agent gets hurt, give a large negative reward
        elif health < 10:
            return -100
        else:
            return 0

    dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, health, past_agent_positions)
    sparse_reward = sparse(current_nearest_blocks, health)

    return np.sign(sparse_reward) * 1 + np.sign(dense_reward) * 0.1
```

Algorithm IV Reward Function Example of Attacking a Cow ⚔️ 🐄 on Plains 🏞️

```python
def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions
    , GLOBAL_DATA, damage_dealt, kill_entity):
    """
    Thoughts:
    - The agent needs to find a cow and approach and kill it. We can give a positive dense reward for approaching
     or attacking a cow.
    - We can give a sparse reward for killing a cow.
    """

    import numpy as np

    def dense(current_nearest_blocks, previous_nearest_blocks, damage_dealt):
        # Reward for approaching the cow
        approach_reward = 0
        if "cow" in current_nearest_blocks and "cow" in previous_nearest_blocks:
            if current_nearest_blocks["cow"][0] < previous_nearest_blocks["cow"][0]:
                approach_reward = 1
            elif current_nearest_blocks["cow"][0] > previous_nearest_blocks["cow"][0]:
                approach_reward = -1

        # Reward for attacking the cow
        if damage_dealt > 0:
            attack_reward = 5
        else:
            attack_reward = 0

        return approach_reward + attack_reward

    def sparse(kill_entity):
        # Reward for killing the cow
        if kill_entity["cow"] > 0:
            return 100
        else:
            return 0

    dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, damage_dealt)
    sparse_reward = sparse(kill_entity)

    return np.sign(sparse_reward) * 1 + np.sign(dense_reward) * 0.1
```

F. Example of Full Interactions with LLM

We show an example of interactions with the LLM for the diamond exploration task, including initializing reward function and one iteration of updating reward function. **INPUT** is the input prompt and **OUTPUT** is the response from GPT-4. We highlight some lines that are related to critic revising and reward updating in yellow.

DESIGNER INPUT:

You are now a proficient Minecraft player. You should help me write proper reward functions to train a Minecraft agent with reinforcement learning to complete the described task.

Task description

- Objective: Find and approach diamond with higher success rate and avoid death.

- Initial Status:
  1. The agent is under ground at y level 11, the most common level to find diamonds.
  2. The agent already has an iron pickaxe.
- Success criteria: The distance to the nearest diamond block is less than 2 meter.

- Procedure: Explore horizontally to find a diamond, face it and approach it.

Input parameters of the reward function

- current_nearest_blocks: nearby block types and nearest distance of each block type at the **current step**. It is a dictionary, consisting of the names, relative distances with the agent, and relative angles (yaw and pitch) with the agent, in the form of: {NAME_1: (DIST_1, YAW_1, PITCH_1), NAME_2: (DIST_2, YAW_2, PITCH_2)}. For example, {"wood": (24.7, 1.48, -1.57), "cobblestone": (1.3, -0.17, 1.05), "iron_ore": (4.5, 0.61, -0.17)}. If a certrain block type does not exist in the field of view, it is not present in the dictionary. The yaw and pitch here is relative to the agent's front, i.e., pitch = 0 and yaw = 0 is the front of the agent.

- previou_nearest_blocks: nearby block types and nearest distance of each block type at the **previous step**, with the same format as the current_nearest_blocks.

- inventory_change: the change of the agent's inventory from the previous step to current step, in the form of a dictionary: {NAME_1: CHANGE_NUM_1, NAME_2: CHANGE_NUM_2}. Positive values mean increase and negative values mean decrease. For example, {"wood": 2, "dirt": 3, "stone_pickaxe": -1}.

- health: an integer value in range 0 to 10 indicating the health level of the agent. 0 means death and 10 means full health.

- past_agent_positions: the history of location of agent, in the form of a list: [[x1, y1, z1, yaw1, pitch1], [x2, y2, z2, yaw2, pitch2], ...]. The yaw and pitch here are relative to the agent's initial forward direction, i.e., pitch = 0 and yaw = 0 is the front of the agent when it was born. The length of the list is the number of steps the agent has taken. The last element of the list is the current location of the agent.

- GLOBAL_DATA: a global variable. It is initialized as a dictionary. You can save necessary information between different steps with it.

General game information

- The version of Minecraft is 1.11.

- Common block names : dirt, cobblestone, iron, diamond, wood, coal, water, air, lava, leaves, ... Collected item names are the same.

- FOV is set to -35 to 35 degrees for yaw and -30 to 30 degrees for pitch. The max visible distance of blocks is 64.

- Length of each block is 1 meter.

- The y coordinate of the agent is the agent's height. The larger the y, the higher the agent. The ground level is around y = 63, but is not fixed.

- At each step, the agent selects one operation in is action space. The action space includes doing nothing (i.e. staying still), moving forward and backward, jumping and attacking. The action space also includes turning left, right, up and down.

- The attack range is 2 meters in front of the agent. The agent can move 0.2 meters in each step. The agent can turn 15 degrees in each step. Typically, the agent needs to stay still and attack for **60 successive steps** to break a block.

- The hunger value is always at the max level.

Reward function requirements

- You should write a dense reward function `dense` and a sparse reward function `sparse`. The sparse reward indicates achieving the goal or receiving heavy punishment. The dense reward provides intermediate signal to guide the agent in the process of achieving the goal. The magnitude of the return value does not matter, but the sign (positive or negative) is important. The final reward will be `np.sign(sparse(...)) * 1 + np.sign(dense(...)) * 0.1`.

Output Requirements

- The reward function should be written in Python 3.9.

- Output the code block only. **Do not output anything else outside the code block**.

- You should include **sufficient comments** in your reward function to explain your thoughts, the objective and **implementation details**. The implementation can be specified to a specific line of code.

- If you need to import packages (e.g. math, numpy) or define helper functions, define them at the beginning of the function. Do not use unimported packages and undefined functions.

Output format

Strictly follow the following format. **Do not output anything else outside the code block**.

```
def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    # Thoughts:
    # ...
    # (import packages and define helper functions)
    import numpy as np
    ...
    def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        ...
    def sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        ...
    dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
    sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
    return np.sign(sparse_reward) * 1 + np.sign(dense_reward) * 0.1
    ...
```

Now write a reward function. Then in each iteration, I will use the reward function to train an RL agent, and test it in the environment. I will give you possible reasons of the failure found during the testing, and you should modify the reward function accordingly.

_____

DESIGNER OUTPUT:

```
def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    """
    Thoughts:
    In order to make the agent approach the diamond, we need to give positive rewards for actions that
    make the agent get closer to the diamond and negative rewards for actions that make the agent get further from the diamond.
    We also need to give a negative reward if the agent's health decreases to encourage the agent to avoid dangerous situations.
    The dense reward function will be based on the distance to the diamond and health.
    The sparse reward function will give a large positive reward when the agent reaches the diamond and a large negative reward
    when the agent dies.
    """
    import numpy as np
    def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
```

```python
    # Initialize reward
    reward = 0
    # If the agent is closer to diamond than before, give a positive reward
    if "diamond" in current_nearest_blocks and "diamond" in previous_nearest_blocks:
        if current_nearest_blocks["diamond"][0] < previous_nearest_blocks["diamond"][0]:
            reward += 1
        elif current_nearest_blocks["diamond"][0] > previous_nearest_blocks["diamond"][0]:
            reward -= 1
    # If the agent's health decreases, give a negative reward
    if health < GLOBAL_DATA["health"]:
        reward -= 1
    GLOBAL_DATA["health"] = health
    return reward
def sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    # Initialize reward
    reward = 0
    # If the agent reaches the diamond, give a large positive reward
    if "diamond" in current_nearest_blocks and current_nearest_blocks["diamond"][0] < 1:
        reward += 100
    # If the agent dies, give a large negative reward
    if health == 0:
        reward -= 100
    return reward
dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
return np.sign(dense_reward) * 1 + np.sign(sparse_reward) * 0.1
```
_____

CRITIC INPUT:

You are now a proficient Minecraft player. I will give you a reward function written in Python, which is used to train an RL agent to play Minecraft.

You should help me to evaluate whether the reward function has met the requirements.

Task description

- Objective: Find and approach diamond with higher success rate and avoid death.

- Initial Status:
  1. The agent is under ground at y level 11, the most common level to find diamonds.
  2. The agent already has an iron pickaxe.
- Success criteria: The distance to the nearest diamond block is less than 2 meter.

- Procedure: Explore horizontally to find a diamond, face it and approach it.

Input parameters of the reward function

- current_nearest_blocks: nearby block types and nearest distance of each block type at the **current step**. It is a dictionary, consisting of the names, relative distances with the agent, and relative angles (yaw and pitch) with the agent, in the form of: {NAME_1: (DIST_1, YAW_1, PITCH_1), NAME_2: (DIST_2, YAW_2, PITCH_2)}. For example, {"wood": (24.7, 1.48, -1.57), "cobblestone": (1.3, -0.17, 1.05), "iron_ore": (4.5, 0.61, -0.17)}. If a certrain block type does not exist in the field of view, it is not present in the dictionary. The yaw and pitch here is relative to the agent's front, i.e., pitch = 0 and yaw = 0 is the front of the agent.

- previou_nearest_blocks: nearby block types and nearest distance of each block type at the **previous step**, with the same format as the current_nearest_blocks.

- inventory_change: the change of the agent's inventory from the previous step to current step, in the form of a dictionary: {NAME_1: CHANGE_NUM_1, NAME_2: CHANGE_NUM_2}. Positive values mean increase and negative values mean decrease. For example, {"wood": 2, "dirt": 3, "stone_pickaxe": -1}.

- health: an integer value in range 0 to 10 indicating the health level of the agent. 0 means death and 10 means full health.

- past_agent_positions: the history of location of agent, in the form of a list: [[x1, y1, z1, yaw1, pitch1], [x2, y2, z2, yaw2, pitch2], ...]. The yaw and pitch here are relative to the agent's initial forward direction, i.e., pitch = 0 and yaw = 0 is the front of the agent when it was born. The length of the list is the number of steps the agent has taken. The last element of the list is the current location of the agent.

- GLOBAL_DATA: a global variable. It is initialized as a dictionary. You can save necessary information between different steps with it.

General game information

- The version of Minecraft is 1.11.

- Common block names : dirt, cobblestone, iron, diamond, wood, coal, water, air, lava, leaves, ... Collected item names are the same.

- FOV is set to -35 to 35 degrees for yaw and -30 to 30 degrees for pitch. The max visible distance of blocks is 64.

- Length of each block is 1 meter.

- The y coordinate of the agent is the agent's height. The larger the y, the higher the agent. The ground level is around y = 63, but is not fixed.

- At each step, the agent selects one operation in is action space. The action space includes doing nothing (i.e. staying still), moving forward and backward, jumping and attacking. The action space also includes turning left, right, up and down.

- The attack range is 2 meters in front of the agent. The agent can move 0.2 meters in each step. The agent can turn 15 degrees in each step. Typically, the agent needs to stay still and attack for **60 successive steps** to break a block.

- The hunger value is always at the max level.

Reward function requirements

- You should write a dense reward function `dense`and a sparse reward function `sparse`. The sparse reward indicates achieving the goal or receiving heavy punishment. The dense reward provides intermediate signal to guide the agent in the process of achieving the goal. The magnitude of the return value does not matter, but the sign (positive or negative) is important. The final reward will be `np.sign(sparse(...)) * 1 + np.sign(dense(...)) * 0.1`.

Requirements

1. You should check whether the reward function meets the **reward function requirements** above.

2. Your judgement should consider whether the comments and the detailed implementation code are consistent. You can judge whether a line is correct by its comment, but do only rely on the comments.

3. You should also check the format of the reward function. It should be like:

```
def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    # Thoughts:
    # ...
    # (import packages and define helper functions)
    import numpy as np
    ...
    def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        ...
    def sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        ...
    dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
    sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
    return np.sign(sparse_reward) * 1 + np.sign(dense_reward) * 0.1
    ...
```

4. Consider the **Information about the game state** above.

5. **You don't need to check whether the reward function meets the task description**.

6. You should first provide a reasoning and decision. If the reward function fails, provide a critique to help to improve the reward function.

Output format

You should only respond in JSON format as described below:

```
{
    "reasoning": "reasoning",
    "success": boolean,
    "critique": critique,
}
```

Ensure the response can be parsed by Python `json.loads`, e.g. no trailing commas, no single quotes, etc. Do not output anything else like explanations.

Reward function to be evaluated

```python
def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    """
    Thoughts:
    In order to make the agent approach the diamond, we need to give positive rewards for actions that
    make the agent get closer to the diamond and negative rewards for actions that make the agent get further from the diamond.
    We also need to give a negative reward if the agent's health decreases to encourage the agent to avoid dangerous situations.
    The dense reward function will be based on the distance to the diamond and health.
    The sparse reward function will give a large positive reward when the agent reaches the diamond and a large negative reward when the agent dies.
    """
    import numpy as np
    def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        # Initialize reward
        reward = 0
        # If the agent is closer to diamond than before, give a positive reward
        if "diamond" in current_nearest_blocks and "diamond" in previous_nearest_blocks:
            if current_nearest_blocks["diamond"][0] < previous_nearest_blocks["diamond"][0]:
                reward += 1
            elif current_nearest_blocks["diamond"][0] > previous_nearest_blocks["diamond"][0]:
                reward -= 1
        # If the agent's health decreases, give a negative reward
        if health < GLOBAL_DATA["health"]:
            reward -= 1
        GLOBAL_DATA["health"] = health
        return reward
    def sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        # Initialize reward
        reward = 0
        # If the agent reaches the diamond, give a large positive reward
        if "diamond" in current_nearest_blocks and current_nearest_blocks["diamond"][0] < 1:
            reward += 100
        # If the agent dies, give a large negative reward
        if health == 0:
            reward -= 100
        return reward
    dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
```

GLOBAL_DATA)
    sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
    return np.sign(dense_reward) * 1 + np.sign(sparse_reward) * 0.1
_____

CRITIC OUTPUT:

{
    "reasoning": "The reward function does not consider that `health` is not initialized in GLOBAL_DATA. It will raise a error because the key `health` is not found.",
    "success": false,
    "critique": "The reward function needs to be revised to initialize `health` in GLOBAL_DATA."
}

_____

DESIGNER INPUT:

The reward function fails to pass the verification. The reasoning is:

```

The reward function does not consider that `health` is not initialized in GLOBAL_DATA. It will raise a error because the key `health` is not found.

```

The critique is:

```

The reward function needs to be revised to initialize `health` in GLOBAL_DATA.

```

Requirements

Please consider the reasoning and critique, and modify the reward function.

1. If necessary, you can write a totally different reward function than the current one.

2. In the first part of the reward function, you should provide your thoughts of modifying the reward function. The thoughts should not directly copy the given reasoning or critique. **The thoughts should be concise.**

Reward function requirements

- You should write a dense reward function `dense` and a sparse reward function `sparse`. The sparse reward indicates achieving the goal or receiving heavy punishment. The dense reward provides intermediate signal to guide the agent in the process of achieving the goal. The magnitude of the return value does not matter, but the sign (positive or negative) is important. The final reward will be `np.sign(sparse(...)) * 1 + np.sign(dense(...)) * 0.1`.

Output format

Strictly follow the following format. **Do not output anything else outside the code block**.

def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    # Thoughts:
    # ...
    # (import packages and define helper functions)
    import numpy as np
    ...
    def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        ...
    def sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        ...

```
    dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
GLOBAL_DATA)
    sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
GLOBAL_DATA)
    return np.sign(sparse_reward) * 1 + np.sign(dense_reward) * 0.1
    ...
```
_____

DESIGNER OUTPUT:

```
def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
GLOBAL_DATA):
    """
    Thoughts:
    In order to make the agent approach the diamond, we need to give positive rewards for actions that
    make the agent get closer to the diamond and negative rewards for actions that make the agent get further from the diamond.
    We also need to give a negative reward if the agent's health decreases to encourage the agent to avoid dangerous situations.
    The dense reward function will be based on the distance to the diamond and health.
    The sparse reward function will give a large positive reward when the agent reaches the diamond and a large negative reward
when the agent dies.
    """
    import numpy as np
    def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
GLOBAL_DATA):
        # Initialize reward
        reward = 0
        # If the agent is closer to diamond than before, give a positive reward
        if "diamond" in current_nearest_blocks and "diamond" in previous_nearest_blocks:
            if current_nearest_blocks["diamond"][0] < previous_nearest_blocks["diamond"][0]:
                reward += 1
            elif current_nearest_blocks["diamond"][0] > previous_nearest_blocks["diamond"][0]:
                reward -= 1
        # If the agent's health decreases, give a negative reward
        if "health" in GLOBAL_DATA:
            if health < GLOBAL_DATA["health"]:
                reward -= 1
        GLOBAL_DATA["health"] = health
        return reward
    def sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
GLOBAL_DATA):
        # Initialize reward
        reward = 0
        # If the agent reaches the diamond, give a large positive reward
        if "diamond" in current_nearest_blocks and current_nearest_blocks["diamond"][0] < 1:
            reward += 100
        # If the agent dies, give a large negative reward
        if health == 0:
            reward -= 100
        return reward
    dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
GLOBAL_DATA)
    sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
GLOBAL_DATA)
    return np.sign(dense_reward) * 1 + np.sign(sparse_reward) * 0.1
```
_____

CRITIC INPUT:

You are now a proficient Minecraft player. I will give you a reward function written in Python, which is used to train an RL agent to play Minecraft.

You should help me to evaluate whether the reward function has met the requirements.

Task description

- Objective: Find and approach diamond with higher success rate and avoid death.

- Initial Status:
  1. The agent is under ground at y level 11, the most common level to find diamonds.
  2. The agent already has an iron pickaxe.
- Success criteria: The distance to the nearest diamond block is less than 2 meter.

- Procedure: Explore horizontally to find a diamond, face it and approach it.

Input parameters of the reward function

- current_nearest_blocks: nearby block types and nearest distance of each block type at the **current step**. It is a dictionary, consisting of the names, relative distances with the agent, and relative angles (yaw and pitch) with the agent, in the form of: {NAME_1: (DIST_1, YAW_1, PITCH_1), NAME_2: (DIST_2, YAW_2, PITCH_2)}. For example, {"wood": (24.7, 1.48, -1.57), "cobblestone": (1.3, -0.17, 1.05), "iron_ore": (4.5, 0.61, -0.17)}. If a certrain block type does not exist in the field of view, it is not present in the dictionary. The yaw and pitch here is relative to the agent's front, i.e., pitch = 0 and yaw = 0 is the front of the agent.

- previou_nearest_blocks: nearby block types and nearest distance of each block type at the **previous step**, with the same format as the current_nearest_blocks.

- inventory_change: the change of the agent's inventory from the previous step to current step, in the form of a dictionary: {NAME_1: CHANGE_NUM_1, NAME_2: CHANGE_NUM_2}. Positive values mean increase and negative values mean decrease. For example, {"wood": 2, "dirt": 3, "stone_pickaxe": -1}.

- health: an integer value in range 0 to 10 indicating the health level of the agent. 0 means death and 10 means full health.

- past_agent_positions: the history of location of agent, in the form of a list: [[x1, y1, z1, yaw1, pitch1], [x2, y2, z2, yaw2, pitch2], ...]. The yaw and pitch here are relative to the agent's initial forward direction, i.e., pitch = 0 and yaw = 0 is the front of the agent when it was born. The length of the list is the number of steps the agent has taken. The last element of the list is the current location of the agent.

- GLOBAL_DATA: a global variable. It is initialized as a dictionary. You can save necessary information between different steps with it.

General game information

- The version of Minecraft is 1.11.

- Common block names : dirt, cobblestone, iron, diamond, wood, coal, water, air, lava, leaves, ... Collected item names are the same.

- FOV is set to -35 to 35 degrees for yaw and -30 to 30 degrees for pitch. The max visible distance of blocks is 64.

- Length of each block is 1 meter.

- The y coordinate of the agent is the agent's height. The larger the y, the higher the agent. The ground level is around y = 63, but is not fixed.

- At each step, the agent selects one operation in is action space. The action space includes doing nothing (i.e. staying still), moving forward and backward, jumping and attacking. The action space also includes turning left, right, up and down.

- The attack range is 2 meters in front of the agent. The agent can move 0.2 meters in each step. The agent can turn 15 degrees in each step. Typically, the agent needs to stay still and attack for **60 successive steps** to break a block.

- The hunger value is always at the max level.

Reward function requirements

- You should write a dense reward function `dense` and a sparse reward function `sparse`. The sparse reward indicates achieving the goal or receiving heavy punishment. The dense reward provides intermediate signal to guide the agent in the process of achieving the goal. The magnitude of the return value does not matter, but the sign (positive or negative) is important. The final reward will be `np.sign(sparse(...)) * 1 + np.sign(dense(...)) * 0.1`.

Requirements

1. You should check whether the reward function meets the **reward function requirements** above.

2. Your judgement should consider whether the comments and the detailed implementation code are consistent. You can judge whether a line is correct by its comment, but do only rely on the comments.

3. You should also check the format of the reward function. It should be like:

```
def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    # Thoughts:
    # ...
    # (import packages and define helper functions)
    import numpy as np
    ...
    def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        ...
    def sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        ...
    dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
    sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
    return np.sign(sparse_reward) * 1 + np.sign(dense_reward) * 0.1
    ...
```

4. Consider the **Information about the game state** above.

5. **You don't need to check whether the reward function meets the task description**.

6. You should first provide a reasoning and decision. If the reward function fails, provide a critique to help to improve the reward function.

Output format

You should only respond in JSON format as described below:

```
{
    "reasoning": "reasoning",
    "success": boolean,
    "critique": critique,
}
```

Ensure the response can be parsed by Python `json.loads`, e.g. no trailing commas, no single quotes, etc. Do not output anything else like explanations.

Reward function to be evaluated

```
def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    """
    Thoughts:
    In order to make the agent approach the diamond, we need to give positive rewards for actions that
    make the agent get closer to the diamond and negative rewards for actions that make the agent get further from the diamond.
    We also need to give a negative reward if the agent's health decreases to encourage the agent to avoid dangerous situations.
    The dense reward function will be based on the distance to the diamond and health.
    The sparse reward function will give a large positive reward when the agent reaches the diamond and a large negative reward
    when the agent dies.
    """
    import numpy as np
    def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        # Initialize reward
```

```python
        reward = 0
        # If the agent is closer to diamond than before, give a positive reward
        if "diamond" in current_nearest_blocks and "diamond" in previous_nearest_blocks:
            if current_nearest_blocks["diamond"][0] < previous_nearest_blocks["diamond"][0]:
                reward += 1
            elif current_nearest_blocks["diamond"][0] > previous_nearest_blocks["diamond"][0]:
                reward -= 1
        # If the agent's health decreases, give a negative reward
        if "health" in GLOBAL_DATA:
            if health < GLOBAL_DATA["health"]:
                reward -= 1
        GLOBAL_DATA["health"] = health
        return reward
    def sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        # Initialize reward
        reward = 0
        # If the agent reaches the diamond, give a large positive reward
        if "diamond" in current_nearest_blocks and current_nearest_blocks["diamond"][0] < 1:
            reward += 100
        # If the agent dies, give a large negative reward
        if health == 0:
            reward -= 100
        return reward
    dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
    sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
    return np.sign(dense_reward) * 1 + np.sign(sparse_reward) * 0.1
```

CRITIC OUTPUT:

{
    "reasoning": "The reward function meets the requirements. It considers sparse reward of completing the objective and death, and dense reward of getting closer to diamond and health decrease.",
    "success": true,
    "critique": null
}

(TRAIN AN AGENT WITH THE REWARD FUNCTION)

ANALYZER INPUT:

You are now a proficient Minecraft player. I have trained an RL agent and tested for several times in the Minecraft game environment.

I will give you the information of the failed test results, i.e. trajectories of actions, rewards and observations. You should help me write proper analysis of possible reasons of failure and inefficiency, and your suggestion on the game strategy.

Task description

- Objective: Find and approach diamond with higher success rate and avoid death.

- Initial Status:
  1. The agent is under ground at y level 11, the most common level to find diamonds.
  2. The agent already has an iron pickaxe.
- Success criteria: The distance to the nearest diamond block is less than 2 meter.

- Procedure: Explore horizontally to find a diamond, face it and approach it.

General game information

- The version of Minecraft is 1.11.

- Common block names : dirt, cobblestone, iron, diamond, wood, coal, water, air, lava, leaves, ... Collected item names are the same.

- FOV is set to -35 to 35 degrees for yaw and -30 to 30 degrees for pitch. The max visible distance of blocks is 64.

- Length of each block is 1 meter.

- The y coordinate of the agent is the agent's height. The larger the y, the higher the agent. The ground level is around y = 63, but is not fixed.

- At each step, the agent selects one operation in is action space. The action space includes doing nothing (i.e. staying still), moving forward and backward, jumping and attacking. The action space also includes turning left, right, up and down.

- The attack range is 2 meters in front of the agent. The agent can move 0.2 meters in each step. The agent can turn 15 degrees in each step. Typically, the agent needs to stay still and attack for **60 successive steps** to break a block.

- The hunger value is always at the max level.

Input format

Failed trajectories

The failed trajectories are shown as a list, where each entry is a dictionary representing a trajectory. Note that **only the failed cases are provided.**

The each item of "history" is a list representing statistics of each single step. When the history is too long, it will be truncated to the last 32 steps, indicated by the value of "truncated".

"dead" indicates whether the agent has died.

The format is:

```
[
    {
        "history": {
            "rewards": [reward1, ...],
            "actions": [action1, action2, ...],
            "locations": [[x1, y1, z1, pitch1, yaw1], ...],
            "inventory_change": {item1: delta_num1, ...},
            "truncated": True or False,
        },
        "final_health": health,
        "final_inventory": {item1: num1, ...},
        "final_nearest_blocks": {block_name1: nearest_distance1, block_name2: nearest_distance2, ...},
        "block_under_foot": block_name,
        "dead": True or False,
    },
    ...
]
```

where "final_health" is in range 0 and 10. "block_under_foot" is the block right under the agent.

Statistics

The statistics is a dictionary of all the test results, including **both successful and failed trajectories**.

The format is:

```
{
    "success_rate" : success_rate,
}
```

Requirements

Please write proper analysis of possible reasons of failure and inefficiency, and your suggestion on the game strategy. You should not not be limited to the task description above, but also come up with other failure cases based on the test results.

The analysis and suggestion should be concise.

Test results

Failed trajectories

```
[{'block_under_foot': 'lava',
 'dead': True,
 'final_health': 0.5,
 'final_inventory': {'coal': 3,
              'cobblestone': 84,
              'crafting_table': 1,
              'furnace': 1,
              'gravel': 3,
              'iron_pickaxe': 1,
              'planks': 2,
              'stone': 17,
              'stone_pickaxe': 10,
              'wooden_pickaxe': 1},
 'final_nearest_blocks': {'lava': [0.01, -0.87, -0.63]},
 'history': {'actions': ['noop', 'attack', 'noop', 'attack', 'noop', 'attack',
              'attack', 'turn_down', 'attack', 'attack', 'noop',
              'attack', 'forward', 'forward', 'noop', 'noop',
              'forward_jump', 'forward_jump', 'attack', 'attack',
              'attack', 'noop', 'jump', 'noop', 'noop', 'jump',
              'attack', 'turn_down', 'turn_up', 'forward_jump',
              'turn_down', 'turn_up'],
        'inventory_change': [{}, {}, {}, {}, {}, {}, {}, {}, {}, {}, {},
                  {}, {}, {}, {}, {}, {}, {}, {}, {}, {},
                  {}, {}, {}, {}, {}, {}, {}, {}, {}, {}],
        'locations': [[-205.42, 9.27, 474.4, 15.0, -90.0],
              [-205.41, 9.24, 474.4, 15.0, -90.0],
              [-205.41, 9.2, 474.4, 15.0, -90.0],
              [-205.41, 9.16, 474.4, 15.0, -90.0],
              [-205.41, 9.12, 474.4, 15.0, -90.0],
              [-205.41, 9.08, 474.4, 15.0, -90.0],
              [-205.41, 9.04, 474.4, 15.0, -90.0],
              [-205.41, 9.0, 474.4, 15.0, -90.0],
              [-205.41, 8.96, 474.4, 30.0, -90.0],
              [-205.41, 8.92, 474.4, 30.0, -90.0],
              [-205.41, 8.88, 474.4, 30.0, -90.0],
              [-205.41, 8.84, 474.4, 30.0, -90.0],
              [-205.41, 8.8, 474.4, 30.0, -90.0],
              [-205.39, 8.76, 474.4, 30.0, -90.0],
              [-205.36, 8.72, 474.4, 30.0, -90.0],
              [-205.34, 8.68, 474.4, 30.0, -90.0],
              [-205.34, 8.64, 474.4, 30.0, -90.0],
              [-205.31, 8.64, 474.4, 30.0, -90.0],
              [-205.3, 8.66, 474.4, 30.0, -90.0],
              [-205.3, 8.65, 474.4, 30.0, -90.0],
              [-205.3, 8.63, 474.4, 30.0, -90.0],
              [-205.3, 8.6, 474.4, 30.0, -90.0],
              [-205.3, 8.56, 474.4, 30.0, -90.0],
              [-205.3, 8.56, 474.4, 30.0, -90.0],
              [-205.3, 8.54, 474.4, 30.0, -90.0],
              [-205.3, 8.51, 474.4, 30.0, -90.0],
```

```
                [-205.3, 8.52, 474.4, 30.0, -90.0],
                [-205.3, 8.5, 474.4, 30.0, -90.0],
                [-205.3, 8.47, 474.4, 45.0, -90.0],
                [-205.3, 8.43, 474.4, 30.0, -90.0],
                [-205.3, 8.44, 474.4, 30.0, -90.0],
                [-205.3, 8.42, 474.4, 45.0, -90.0]],
       'nearest_blocks': [{'lava': [0.25, 0.87, -0.63]},
                {'lava': [0.31, 0.87, -0.63]},
                {'lava': [0.38, 0.87, -0.63]},
                {'lava': [0.41, 0.07, -0.03]},
                {'lava': [0.41, 0.07, -0.03]},
                {'lava': [0.41, 0.07, -0.03]},
                {'lava': [0.41, 0.07, -0.03]},
                {'lava': [0.41, 0.35, -0.1]},
                {'lava': [0.41, 0.35, -0.1]},
                {'lava': [0.41, 0.35, -0.1]},
                {'lava': [0.41, 0.35, -0.1]},
                {'lava': [0.41, 0.35, -0.1]},
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                {'lava': [0.34, -1.57, 0.0]},
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                {'lava': [0.26, -1.57, 0.0]},
                {'lava': [0.28, -1.57, 0.0]},
                {'lava': [0.27, -1.57, 0.0]},
                {'lava': [0.25, -0.87, -0.63]},
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                {'lava': [0.18, -0.87, -0.63]},
                {'lava': [0.18, -0.87, -0.63]},
                {'lava': [0.16, -0.87, -0.63]},
                {'lava': [0.13, -0.87, -0.63]},
                {'lava': [0.14, -0.87, -0.63]},
                {'lava': [0.12, -0.87, -0.63]},
                {'lava': [0.09, -0.87, -0.63]},
                {'lava': [0.05, -1.57, 0.0]},
                {'lava': [0.06, -0.87, -0.63]},
                {'lava': [0.04, -0.87, -0.63]},
                {'lava': [0.01, -0.87, -0.63]}],
       'rewards': [],
       'truncated': True}},
{'block_under_foot': 'stone',
 'dead': False,
 'final_health': 10.0,
 'final_inventory': {'coal': 5,
             'cobblestone': 133,
             'crafting_table': 1,
             'dirt': 18,
             'furnace': 1,
             'iron_pickaxe': 1,
             'planks': 2,
             'stone': 37,
             'stone_pickaxe': 9,
             'wooden_pickaxe': 1},
 'final_nearest_blocks': {'stone': [0.5, 0.87, -0.63]},
 'history': {'actions': ['attack', 'attack', 'attack', 'attack', 'attack',
                'attack', 'attack', 'attack', 'attack', 'attack',
```

```
        'attack', 'attack', 'attack', 'attack', 'attack',
        'noop', 'turn_up', 'turn_up', 'turn_up', 'noop',
        'forward', 'forward', 'forward', 'forward', 'forward',
        'forward', 'back', 'noop', 'noop', 'attack', 'attack',
        'attack'],
'inventory_change': [{}, {}, {}, {'cobblestone': 1}, {}, {}, {},
            {}, {}, {}, {}, {}, {}, {}, {}, {}, {}, {},
            {}, {}, {}, {}, {}, {}, {'cobblestone': 1},
            {}, {}, {}, {}, {}, {}, {}],
'locations': [[611.54, 11.0, 212.67, 45.0, -180.0],
        [611.54, 11.0, 212.67, 45.0, -180.0],
        [611.54, 11.0, 212.67, 45.0, -180.0],
        [611.54, 11.0, 212.67, 45.0, -180.0],
        [611.54, 11.0, 212.67, 45.0, -180.0],
        [611.54, 11.0, 212.67, 45.0, -180.0],
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        [611.54, 11.0, 212.67, 45.0, -180.0],
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        [611.54, 11.0, 212.67, 45.0, -180.0],
        [611.54, 11.0, 212.67, 45.0, -180.0],
        [611.54, 11.0, 212.67, 45.0, -180.0],
        [611.54, 11.0, 212.67, 45.0, -180.0],
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        [611.54, 11.0, 212.67, 0.0, -180.0],
        [611.54, 11.0, 212.57, 0.0, -180.0],
        [611.54, 11.0, 212.42, 0.0, -180.0],
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        [611.54, 11.0, 211.84, 0.0, -180.0],
        [611.54, 11.0, 211.63, 0.0, -180.0],
        [611.54, 11.0, 211.61, 0.0, -180.0],
        [611.54, 11.0, 211.6, 0.0, -180.0],
        [611.54, 11.0, 211.6, 0.0, -180.0],
        [611.54, 11.0, 211.6, 0.0, -180.0],
        [611.54, 11.0, 211.6, 0.0, -180.0]],
'nearest_blocks': [{'stone': [0.78, 0.73, -0.63]},
            {'stone': [0.78, 0.73, -0.63]},
            {'stone': [0.78, 0.73, -0.63]},
            {'stone': [0.78, 0.73, -0.63]},
            {'stone': [0.78, 0.73, -0.63]},
            {'stone': [0.78, 0.73, -0.63]},
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            {'stone': [0.78, 0.73, -0.63]},
            {'stone': [0.78, 0.73, -0.63]},
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            {'stone': [0.78, 0.73, -0.63]},
            {'stone': [0.78, 0.73, -0.63]},
```

                {'stone': [0.78, 0.73, -0.63]},
                {'stone': [0.78, 0.49, -0.63]},
                {'stone': [0.66, 0.87, -0.63]},
                {'stone': [0.5, 0.87, -0.63]},
                {'stone': [0.5, 0.87, -0.63]},
                {'stone': [0.5, 0.87, -0.63]},
                {'stone': [0.5, 0.87, -0.63]},
                {'stone': [0.5, 0.87, -0.63]},
                {'stone': [0.5, 0.87, -0.63]},
                {'stone': [0.5, 0.87, -0.63]},
                {'stone': [0.5, 0.87, -0.63]},
                {'stone': [0.5, 0.87, -0.63]},
                {'stone': [0.5, 0.87, -0.63]},
                {'stone': [0.5, 0.87, -0.63]},
                {'stone': [0.5, 0.87, -0.63]},
                {'stone': [0.5, 0.87, -0.63]}],
          'rewards': [],
          'truncated': True}}]
Statistics

{'success_rate': 0.0}

_____

ANALYZER OUTPUT:

Analysis of Possible Reasons of Failure and Inefficiency: In one of the failed trajectories, the agent died due to lava. The agent did not take any action to avoid the lava or move away from it. The agent should be programmed to detect and avoid dangerous blocks, such as lava, by turning or moving in a different direction.

Suggestion on Game Strategy: Train the agent to detect and avoid dangerous blocks, such as lava or deep holes. The agent should be programmed to prioritize safety and avoid situations that could lead to death or loss of health.

By implementing the suggestion and improving the agent's training, the success rate of finding diamonds can be increased.

_____

DESIGNER INPUT:

You are now a proficient Minecraft player. I now have a reward function to train a Minecraft agent with reinforcement learning to complete the described task. The reward function is used to train the reinforcement learning agent for several times. I will provide you the analysis of failure and inefficiency and suggestions. You should help me modify the reward function.

Task description

- Objective: Find and approach diamond with higher success rate and avoid death.

- Initial Status:
  1. The agent is under ground at y level 11, the most common level to find diamonds.
  2. The agent already has an iron pickaxe.
- Success criteria: The distance to the nearest diamond block is less than 2 meter.

- Procedure: Explore horizontally to find a diamond, face it and approach it.

Input parameters of the reward function

- current_nearest_blocks: nearby block types and nearest distance of each block type at the **current step**. It is a dictionary, consisting of the names, relative distances with the agent, and relative angles (yaw and pitch) with the agent, in the form of: {NAME_1: (DIST_1, YAW_1, PITCH_1), NAME_2: (DIST_2, YAW_2, PITCH_2)}. For example, {"wood": (24.7, 1.48, -1.57), "cobblestone": (1.3, -0.17, 1.05), "iron_ore": (4.5, 0.61, -0.17)}. If a certrain block type does not exist in the field of view, it is not present in the dictionary. The yaw and pitch here is relative to the agent's front, i.e., pitch = 0 and yaw = 0 is the front of the agent.

- previou_nearest_blocks: nearby block types and nearest distance of each block type at the **previous step**, with the same format as the current_nearest_blocks.

- inventory_change: the change of the agent's inventory from the previous step to current step, in the form of a dictionary: {NAME_1: CHANGE_NUM_1, NAME_2: CHANGE_NUM_2}. Positive values mean increase and negative values mean decrease. For example, {"wood": 2, "dirt": 3, "stone_pickaxe": -1}.

- health: an integer value in range 0 to 10 indicating the health level of the agent. 0 means death and 10 means full health.

- past_agent_positions: the history of location of agent, in the form of a list: [[x1, y1, z1, yaw1, pitch1], [x2, y2, z2, yaw2, pitch2], ...]. The yaw and pitch here are relative to the agent's initial forward direction, i.e., pitch = 0 and yaw = 0 is the front of the agent when it was born. The length of the list is the number of steps the agent has taken. The last element of the list is the current location of the agent.

- GLOBAL_DATA: a global variable. It is initialized as a dictionary. You can save necessary information between different steps with it.

General game information

- The version of Minecraft is 1.11.

- Common block names : dirt, cobblestone, iron, diamond, wood, coal, water, air, lava, leaves, ... Collected item names are the same.

- FOV is set to -35 to 35 degrees for yaw and -30 to 30 degrees for pitch. The max visible distance of blocks is 64.

- Length of each block is 1 meter.

- The y coordinate of the agent is the agent's height. The larger the y, the higher the agent. The ground level is around y = 63, but is not fixed.

- At each step, the agent selects one operation in is action space. The action space includes doing nothing (i.e. staying still), moving forward and backward, jumping and attacking. The action space also includes turning left, right, up and down.

- The attack range is 2 meters in front of the agent. The agent can move 0.2 meters in each step. The agent can turn 15 degrees in each step. Typically, the agent needs to stay still and attack for **60 successive steps** to break a block.

- The hunger value is always at the max level.

Reward function requirements

- You should write a dense reward function `dense` and a sparse reward function `sparse`. The sparse reward indicates achieving the goal or receiving heavy punishment. The dense reward provides intermediate signal to guide the agent in the process of achieving the goal. The magnitude of the return value does not matter, but the sign (positive or negative) is important. The final reward will be `np.sign(sparse(...)) * 1 + np.sign(dense(...)) * 0.1`.

Current reward function

```
def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    """
    Thoughts:
    In order to make the agent approach the diamond, we need to give positive rewards for actions that
    make the agent get closer to the diamond and negative rewards for actions that make the agent get further from the diamond.
    We also need to give a negative reward if the agent's health decreases to encourage the agent to avoid dangerous situations.
    The dense reward function will be based on the distance to the diamond and health.
    The sparse reward function will give a large positive reward when the agent reaches the diamond and a large negative reward
    when the agent dies.
    """
    import numpy as np
    def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        # Initialize reward
        reward = 0
        # If the agent is closer to diamond than before, give a positive reward
        if "diamond" in current_nearest_blocks and "diamond" in previous_nearest_blocks:
            if current_nearest_blocks["diamond"][0] < previous_nearest_blocks["diamond"][0]:
                reward += 1
            elif current_nearest_blocks["diamond"][0] > previous_nearest_blocks["diamond"][0]:
```

```
          reward -= 1
      # If the agent's health decreases, give a negative reward
      if "health" in GLOBAL_DATA:
          if health < GLOBAL_DATA["health"]:
              reward -= 1
      GLOBAL_DATA["health"] = health
      return reward
  def   sparse(current_nearest_blocks,   previous_nearest_blocks,   inventory_change,   health,   past_agent_positions,
GLOBAL_DATA):
      # Initialize reward
      reward = 0
      # If the agent reaches the diamond, give a large positive reward
      if "diamond" in current_nearest_blocks and current_nearest_blocks["diamond"][0] < 1:
          reward += 100
      # If the agent dies, give a large negative reward
      if health == 0:
          reward -= 100
      return reward
  dense_reward  =  dense(current_nearest_blocks,  previous_nearest_blocks,  inventory_change,  health,  past_agent_positions,
GLOBAL_DATA)
  sparse_reward  =  sparse(current_nearest_blocks,  previous_nearest_blocks,  inventory_change,  health,  past_agent_positions,
GLOBAL_DATA)
  return np.sign(dense_reward) * 1 + np.sign(sparse_reward) * 0.1
```

Reward function test result

The reward function is used to train the reinforcement learning agent for several times. Here is some analysis of failure and inefficiency and suggestions:

```
Analysis of Possible Reasons of Failure and Inefficiency: In one of the failed trajectories, the agent died due to lava. The agent did not take any action to avoid the lava or move away from it. The agent should be programmed to detect and avoid dangerous blocks, such as lava, by turning or moving in a different direction.

Suggestion on Game Strategy: Train the agent to detect and avoid dangerous blocks, such as lava or deep holes. The agent should be programmed to prioritize safety and avoid situations that could lead to death or loss of health.

By implementing the suggestion and improving the agent's training, the success rate of finding diamonds can be increased.
```

Requirements

Please consider the analysis and suggestions above and modify the reward function.

1. You can both modify the current lines and add new lines.

2. If necessary, you can write a **totally different** reward function than the current one.

3. Consider modifing the reward and penalty values in the current reward function to balance them.

4. In the first part of the reward function, you should provide your thoughts of modifying the reward function. **The thoughts should be concise.**

Output format

Strictly follow the following format. **Do not output anything else outside the code block**.

```
def  reward_function(current_nearest_blocks,  previous_nearest_blocks,  inventory_change,  health,  past_agent_positions,
GLOBAL_DATA):
  # Thoughts:
  # ...
  # (import packages and define helper functions)
  import numpy as np
  ...
```

```
    def    dense(current_nearest_blocks,    previous_nearest_blocks,    inventory_change,    health,    past_agent_positions,
GLOBAL_DATA):
        ...
    def    sparse(current_nearest_blocks,    previous_nearest_blocks,    inventory_change,    health,    past_agent_positions,
GLOBAL_DATA):
        ...
    dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
GLOBAL_DATA)
    sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
GLOBAL_DATA)
    return np.sign(sparse_reward) * 1 + np.sign(dense_reward) * 0.1
    ...
```

_____

DESIGNER OUTPUT:

```
def   reward_function(current_nearest_blocks,   previous_nearest_blocks,   inventory_change,   health,   past_agent_positions,
GLOBAL_DATA):
    """
    Thoughts:
    In order to make the agent approach the diamond, we need to give positive rewards for actions that
    make the agent get closer to the diamond and negative rewards for actions that make the agent get further from the diamond.
    We also need to give a negative reward if the agent's health decreases to encourage the agent to avoid dangerous situations.
    The dense reward function will be based on the distance to the diamond and health.
    The sparse reward function will give a large positive reward when the agent reaches the diamond and a large negative reward
when the agent dies.
    In addition, we should implement a threat detection mechanism to avoid unnecessary deaths.
    """
    import numpy as np
    def    dense(current_nearest_blocks,    previous_nearest_blocks,    inventory_change,    health,    past_agent_positions,
GLOBAL_DATA):
        # Initialize reward
        reward = 0
        # If the agent is closer to diamond than before, give a positive reward
        if "diamond" in current_nearest_blocks and "diamond" in previous_nearest_blocks:
            if current_nearest_blocks["diamond"][0] < previous_nearest_blocks["diamond"][0]:
                reward += 1
            elif current_nearest_blocks["diamond"][0] > previous_nearest_blocks["diamond"][0]:
                reward -= 1
        # If the agent is close to lava, give a negative reward
        if "lava" in current_nearest_blocks:
            reward -= 1
        # If the agent's health decreases, give a negative reward
        if "health" in GLOBAL_DATA:
            if health < GLOBAL_DATA["health"]:
                reward -= 1
        GLOBAL_DATA["health"] = health
        return reward
    def    sparse(current_nearest_blocks,    previous_nearest_blocks,    inventory_change,    health,    past_agent_positions,
GLOBAL_DATA):
        # Initialize reward
        reward = 0
        # If the agent reaches the diamond, give a large positive reward
        if "diamond" in current_nearest_blocks and current_nearest_blocks["diamond"][0] < 1:
            reward += 100
        # If the agent dies, give a large negative reward
        if health == 0:
            reward -= 100
```

```
        return reward
    dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
GLOBAL_DATA)
    sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
GLOBAL_DATA)
    return np.sign(dense_reward) * 1 + np.sign(sparse_reward) * 0.1
```
_____

CRITIC INPUT:

You are now a proficient Minecraft player. I will give you a reward function written in Python, which is used to train an RL agent to play Minecraft.

You should help me to evaluate whether the reward function has met the requirements.

Task description

- Objective: Find and approach diamond with higher success rate and avoid death.

- Initial Status:
  1. The agent is under ground at y level 11, the most common level to find diamonds.
  2. The agent already has an iron pickaxe.
- Success criteria: The distance to the nearest diamond block is less than 2 meter.

- Procedure: Explore horizontally to find a diamond, face it and approach it.

Input parameters of the reward function

- current_nearest_blocks: nearby block types and nearest distance of each block type at the **current step**. It is a dictionary, consisting of the names, relative distances with the agent, and relative angles (yaw and pitch) with the agent, in the form of: {NAME_1: (DIST_1, YAW_1, PITCH_1), NAME_2: (DIST_2, YAW_2, PITCH_2)}. For example, {"wood": (24.7, 1.48, -1.57), "cobblestone": (1.3, -0.17, 1.05), "iron_ore": (4.5, 0.61, -0.17)}. If a certrain block type does not exist in the field of view, it is not present in the dictionary. The yaw and pitch here is relative to the agent's front, i.e., pitch = 0 and yaw = 0 is the front of the agent.

- previou_nearest_blocks: nearby block types and nearest distance of each block type at the **previous step**, with the same format as the current_nearest_blocks.

- inventory_change: the change of the agent's inventory from the previous step to current step, in the form of a dictionary: {NAME_1: CHANGE_NUM_1, NAME_2: CHANGE_NUM_2}. Positive values mean increase and negative values mean decrease. For example, {"wood": 2, "dirt": 3, "stone_pickaxe": -1}.

- health: an integer value in range 0 to 10 indicating the health level of the agent. 0 means death and 10 means full health.

- past_agent_positions: the history of location of agent, in the form of a list: [[x1, y1, z1, yaw1, pitch1], [x2, y2, z2, yaw2, pitch2], ...]. The yaw and pitch here are relative to the agent's initial forward direction, i.e., pitch = 0 and yaw = 0 is the front of the agent when it was born. The length of the list is the number of steps the agent has taken. The last element of the list is the current location of the agent.

- GLOBAL_DATA: a global variable. It is initialized as a dictionary. You can save necessary information between different steps with it.

General game information

- The version of Minecraft is 1.11.

- Common block names : dirt, cobblestone, iron, diamond, wood, coal, water, air, lava, leaves, ... Collected item names are the same.

- FOV is set to -35 to 35 degrees for yaw and -30 to 30 degrees for pitch. The max visible distance of blocks is 64.

- Length of each block is 1 meter.

- The y coordinate of the agent is the agent's height. The larger the y, the higher the agent. The ground level is around y = 63, but is not fixed.

- At each step, the agent selects one operation in is action space. The action space includes doing nothing (i.e. staying still), moving forward and backward, jumping and attacking. The action space also includes turning left, right, up and down.

- The attack range is 2 meters in front of the agent. The agent can move 0.2 meters in each step. The agent can turn 15 degrees in each step. Typically, the agent needs to stay still and attack for **60 successive steps** to break a block.

- The hunger value is always at the max level.

Reward function requirements

- You should write a dense reward function `dense`and a sparse reward function `sparse`. The sparse reward indicates achieving the goal or receiving heavy punishment. The dense reward provides intermediate signal to guide the agent in the process of achieving the goal. The magnitude of the return value does not matter, but the sign (positive or negative) is important. The final reward will be `np.sign(sparse(...)) * 1 + np.sign(dense(...)) * 0.1`.

Requirements

1. You should check whether the reward function meets the **reward function requirements** above.

2. Your judgement should consider whether the comments and the detailed implementation code are consistent. You can judge whether a line is correct by its comment, but do only rely on the comments.

3. You should also check the format of the reward function. It should be like:

```
def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    # Thoughts:
    # ...
    # (import packages and define helper functions)
    import numpy as np
    ...
    def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        ...
    def sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
        ...
    dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
    sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA)
    return np.sign(sparse_reward) * 1 + np.sign(dense_reward) * 0.1
    ...
```

4. Consider the **Information about the game state** above.

5. **You don't need to check whether the reward function meets the task description**.

6. You should first provide a reasoning and decision. If the reward function fails, provide a critique to help to improve the reward function.

Output format

You should only respond in JSON format as described below:

```
{
  "reasoning": "reasoning",
  "success": boolean,
  "critique": critique,
}
```

Ensure the response can be parsed by Python `json.loads`, e.g. no trailing commas, no single quotes, etc. Do not output anything else like explanations.

Reward function to be evaluated

```
def reward_function(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions, GLOBAL_DATA):
    """
    Thoughts:
```

In order to make the agent approach the diamond, we need to give positive rewards for actions that
make the agent get closer to the diamond and negative rewards for actions that make the agent get further from the diamond.
We also need to give a negative reward if the agent's health decreases to encourage the agent to avoid dangerous situations.
The dense reward function will be based on the distance to the diamond and health.
The sparse reward function will give a large positive reward when the agent reaches the diamond and a large negative reward
when the agent dies.
In addition, we should implement a threat detection mechanism to avoid unnecessary deaths.
"""

```python
import numpy as np
def dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
GLOBAL_DATA):
    # Initialize reward
    reward = 0
    # If the agent is closer to diamond than before, give a positive reward
    if "diamond" in current_nearest_blocks and "diamond" in previous_nearest_blocks:
        if current_nearest_blocks["diamond"][0] < previous_nearest_blocks["diamond"][0]:
            reward += 1
        elif current_nearest_blocks["diamond"][0] > previous_nearest_blocks["diamond"][0]:
            reward -= 1
    # If the agent is close to lava, give a negative reward
    if "lava" in current_nearest_blocks:
        reward -= 1
    # If the agent's health decreases, give a negative reward
    if "health" in GLOBAL_DATA:
        if health < GLOBAL_DATA["health"]:
            reward -= 1
    GLOBAL_DATA["health"] = health
    return reward
def sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
GLOBAL_DATA):
    # Initialize reward
    reward = 0
    # If the agent reaches the diamond, give a large positive reward
    if "diamond" in current_nearest_blocks and current_nearest_blocks["diamond"][0] < 1:
        reward += 100
    # If the agent dies, give a large negative reward
    if health == 0:
        reward -= 100
    return reward
dense_reward = dense(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
GLOBAL_DATA)
sparse_reward = sparse(current_nearest_blocks, previous_nearest_blocks, inventory_change, health, past_agent_positions,
GLOBAL_DATA)
return np.sign(dense_reward) * 1 + np.sign(sparse_reward) * 0.1
```
_____

CRITIC OUTPUT:

```
{
    "reasoning": "The reward function meets the requirements. It considers sparse reward of completing the objective and death,
and dense reward of getting closer to diamond, having lava nearby and health decrease.",
    "success": true,
    "critique": null
}
```