Generalization in Text-based Games via Hierarchical Reinforcement Learning

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Abstract

Deep reinforcement learning provides a promising approach for text-based games in studying natural language communication between humans and artificial agents. However, the generalization still remains a big challenge as the agents depend critically on the complexity and variety of training tasks. In this paper, we address this problem by introducing a hierarchical framework built upon the knowledge graph-based RL agent. In the high level, a meta-policy is executed to decompose the whole game into a set of subtasks specified by textual goals, and select one of them based on the KG. Then a subpolicy in the low level is executed to conduct goal-conditioned reinforcement learning. We carry out experiments on games with various difficulty levels and show that the proposed method enjoys favorable generalizability.

1 Introduction

Text-based games are simulated systems where the agent takes textual observations as the input, and interacts with the environment via text commands (Hausknecht et al., 2020). They are suitable test-beds to study natural language understanding, commonsense reasoning and language-informed decision making (Luketina et al., 2019). Reinforcement Learning (RL) based agents (Narasimhan et al., 2015; Zahavy et al., 2018) have been developed to handle challenges such as languagebased representation learning and combinatorial action space. Among them, KG-based agents (Ammanabrolu and Hausknecht, 2020) yield promising performance with the aid of Knowledge Graph (KG), which serves as a belief state to provide structural information.

To design intelligent RL-based agents for text-based games, it is necessary to build agents that automatically learn to solve different games. However, generalization remains as one of the key challenges of RL — the agent tends to overfit the train-

ing environment and fails to generalize to new environments (Cobbe et al., 2019). In the domain of text-based games, the TextWorld (Côté et al., 2018) makes it feasible to study generalizability by creating non-overlapping game sets with customizable domain gaps (e.g., themes, vocabulary sets, difficulty levels and layouts). Most previous works study generalizability either upon games with the same difficulty level but different layouts (Ammanabrolu and Riedl, 2019a), or upon games with a set of multiple levels that have been observed during training (Adolphs and Hofmann, 2020). Although these agents perform well on relatively simple games, they can hardly achieve satisfactory performance on difficult games (Adhikari et al., 2020). In this work, we aim to develop agents that can be generalized to not only games from the same difficulty level while having unseen different layouts, but also games from unseen difficulty levels where both layouts and complexities are different.

While solving a whole game might be difficult due to long-term temporal dependencies, and the learnt strategy might be difficult to be transferred to other games due to large domain gaps, it would be more flexible to treat the game as a sketch of subtasks (Andreas et al., 2017; Oh et al., 2017). This brings two branches of benefits. First, the subtasks would be easier to solve as they have shortterm temporal dependencies. Second, the strategies learnt for solving subtasks may be recomposed to solve an unseen game. Motivated by these insights, we aim to solve a game by decomposing it into subtasks characterized by textual goals, then making decisions conditioned on them. Instead of handcrafting the task sketches, we leverage the hierarchical reinforcement learning (HRL) framework for adaptive goal selection, and exploit the compositional nature of language (Jiang et al., 2019) to improve generalizability.

We develop a two-level framework, Hierarchical

Knowledge Graph-based Agent (H-KGA)¹, to learn a hierarchy of policies with the aid of KG. In the high level, we use a meta-policy to obtain a set of available goals characterized by texts, and select one of them according to the current KG-based observation. Then, we use a sub-policy for goal-conditioned reinforcement learning. Besides, we design a scheduled training strategy to facilitate learning across multiple levels. We conduct experiments on a series of cooking games across 8 levels, while only 4 levels are available during training. The experimental results show that our method improves generalizability in both seen and unseen levels.

Our contributions are summarised as follows: Firstly, we are the first to study generalizability in text-based games from the aspect of hierarchical reinforcement learning. Secondly, we develop a two-level HRL framework leveraging the KG-based observation for adaptive goal selection and goal-conditioned decision making. Thirdly, we empirically validate the effectiveness of our method in games with both seen and unseen difficulty levels, which show favorable generalizability.

2 Related work

2.1 RL agent for text-based games

Motivated by the prosperity of deep reinforcement learning techniques in playing games (Silver et al., 2016), robotics (Schulman et al., 2017; Fang et al., 2019a,b) and NLP (Fang et al., 2017), several RLbased game agents have been developed for textbased games (He et al., 2016; Yuan et al., 2018; Jain et al., 2020; Yin and May, 2019; Guo et al., 2020; Xu et al., 2020a). Compared with the nonlearning-based agents (Hausknecht et al., 2019; Atkinson et al., 2019), the RL-based agents are more favorable as there is no need to handcraft game playing strategies with huge amounts of expert knowledge. The KG-based agents (Murugesan et al., 2020; Xu et al., 2020b) extend RL-based agents with the knowledge graph, which can be constructed from the raw textual observation via simple rules (Ammanabrolu and Riedl, 2019a), language models (Ammanabrolu et al., 2020) or pretraining tasks (Adhikari et al., 2020). The major benefit of KG is that it serves as a belief state to provide structural and historical information to handle partial observability. While these works focus

on constructing KG from the textual observation, we aim at improving generalizability by fully exploiting the KG to design a goal-conditioned HRL. Our work thus complements KG-based agents.

2.2 Generalization in text-based games

It may be difficult to study generalization in games initially designed for human players (Hausknecht et al., 2020), as they are so challenging that existing RL agents are still far from being able to solve a large proportion of them even under the single game setting (Yao et al., 2020). Furthermore, these games usually have different themes, vocabularies and logics, making it hard to determine the domain gap (Ammanabrolu and Riedl, 2019b). Compared with these man-made games, the synthetic games (Côté et al., 2018; Urbanek et al., 2019) provide a more natural way to study generalization by generating multiple similar games with customizable domain gaps (e.g., by varying game layouts). Generally, the training and testing game sets in previous works have either the same difficulty level (Ammanabrolu and Riedl, 2019a; Murugesan et al., 2021), or a mixture of multiple levels (Adolphs and Hofmann, 2020; Yin et al., 2020), or both (Adhikari et al., 2020). In this work, we extend the setting of multiple levels to unseen levels. We not only study generalization in games that have the same difficulty level but various layouts, but also consider games where both the layouts and levels are different from those of the training games. In addition, we emphasize on improving the performance on hard levels.

2.3 Hierarchical reinforcement learning

The HRL framework (Dayan and Hinton, 1992) has been studied in video games (Kulkarni et al., 2016; Vezhnevets et al., 2017; Shu et al., 2018), robotic control tasks (Nachum et al., 2018), and NLP tasks such as the dialogue system (Peng et al., 2017; Saleh et al., 2020). However, as far as we know, we are the first to introduce the insight into textbased games with KG-based observation. Previous works also considered identifying a task by textual goal specifications (Bahdanau et al., 2019; Fu et al., 2019). In the domain of text-based games, such goal-conditioned RL setting has been studied with the quest generation tasks (Ammanabrolu et al., 2019, 2021). In our work, we specify a subtask by its goal. Different from these works, where a single goal is pre-specified or directly generated from the observation, we introduce a hierarchy by

¹Code is available at: https://github.com/ YunqiuXu/H-KGA

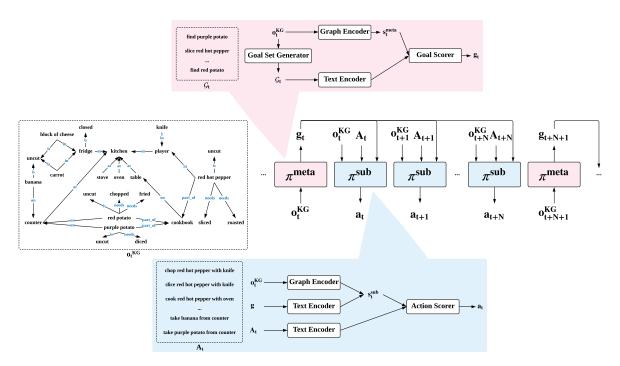


Figure 1: The overview of H-KGA. In the high level (red), the meta-policy π^{meta} first obtains the set of goals of available subtasks \mathcal{G}_t from o_t^{KG} , then selects a goal g_t for the sub-policy π^{sub} . In the low level (blue), π^{sub} selects the action a_t from the admissible action set A_t conditioned on o_t^{KG} and g.

disentangling the process of goal set generation and goal selection. By accommodating flexible goal set generation (e.g., by pre-trained language models or human experts), we focus on designing a metapolicy to select the goal in an adaptive manner. By adopting HRL to select a textual-based goal for the sub-policy, our work is similar to HIN (Jiang et al., 2019) which, however, focuses on visual scenarios and separately trains the meta-policy and the sub-policy, leaving joint training as future work. Instead, we consider the domain of text-based games, and develop a framework to enable joint training of meta-policy and sub-policy. We further compare joint and individual training in Sec. 6.

3 Background

3.1 KG-based observation

Following previous works (Hausknecht et al., 2020), we formulate the text-based games as Partially Observable Markov Decision Processes (POMDPs), where the details is in Appendix A. We discard the raw textual observation and consider only the KG-based observation $o_t^{\rm KG}$ as the observational input at timestep t. Fig. 1 shows an example of $o_t^{\rm KG}$. The KG is defined as G=(V,E), where V and E are the node set and the edge set, respectively. $o_t^{\rm KG}$ consists of a set of

triplets, where a triplet is formulated as $\langle Subject, Relation, Object \rangle$, denoting that the $Subject \in V$ has $Relation \in E$ with the $Object \in V$.

3.2 Problem setting

We aim to design an RL-based agent that is able to address the generalization in solving text-based games. To reduce the requirement for external knowledge, we consider games sharing similar themes and vocabularies, but varying in their layouts and / or difficulty levels. For example, games of the cooking theme (Côté et al., 2018) share the same overall objective: prepare the meal. To accomplish it, the player has to collect ingredients and prepare them in correct ways. The layout of a game contains the room connectivity and the preparing steps (e.g., the type / location of ingredients). The difficulty of a game depends on the complexity of the map (e.g., the number of rooms) and the recipe (e.g., the number of ingredients), such that two games with different levels are naturally different in their layouts. We follow the multi-task learning setting to consider that the training set and the testing set consist of multiple games from multiple levels. We consider two scenarios of generalization: 1) seen levels, where the training and testing games have the same levels, but different layouts. 2) unseen levels, where the training and

testing games are different in levels and layouts. More examples are provided in Appendix. D.

4 Methodology

4.1 Overview

Fig. 1 shows the overview of H-KGA, which consists of a hierarchy of two levels of policies. In the high level, a meta-policy π^{meta} first obtains the set of goals of available subtasks \mathcal{G}_t from o_t^{KG} , then selects a goal g_t for the sub-policy π^{sub} . In the low level, π^{sub} selects the action a_t from the admissible action set A_t conditioned on o_t^{KG} and g. We omit the subscript "t" for g because this goal may be selected in the past rather than the current time step. For example, as shown in Fig. 1, once the g_t is selected by π^{meta} , it will remain unchanged for N time steps until being completed (e.g., accomplished or failed). At each time step from t to t+N, π^{sub} considers the same goal g_t .

In the following, we illustrate how to design π^{meta} to obtain the available goal set \mathcal{G}_t and conduct goal selection to obtain $g_t \in \mathcal{G}_t$ in Sec. 4.2; how to design π^{sub} to select an action $a_t \in A_t$ in Sec. 4.3; and how to train H-KGA with a scheduled curriculum for multi-task learning in Sec. 4.4.

4.2 Meta-policy for goal selection

As discussed before, while a whole game may be difficult to accomplish due to long-term temporal dependency, decomposing it into a sketch of subtasks will make the game easier to be solved (Sohn et al., 2018; Shiarlis et al., 2018). If we consider the solving strategy for a subtask as a skill, the generalizability for an unseen game will also be improved by recomposing the learnt skills. Therefore, inspired by the HRL framework (Sutton et al., 1999), we design a meta-policy π^{meta} to first obtain a set of subtasks, then select one subtask from them. We characterize a subtask by its goal to transform subtask selection into goal selection. We make the goal to be instruction-like textual descriptions (e.g., "find purple potato"), yielding better flexibility and interpretability than using a state as the goal (Andrychowicz et al., 2017). Fig. 1 shows the overview of π^{meta} (in red), which consists of a goal set generator, a graph encoder, a text encoder and a goal scorer. We denote the set containing all required goals for solving a game as G. Then we define a goal as "available" at a time step if no other goals should be accomplished before it. For example, "cook red potato" is not available in

Fig. 1, as another goal "find red potato" should be accomplished first. The goal set generator has two purposes: 1) obtain the set of currently available goals $\mathcal{G}_t \subseteq \mathcal{G}$, and 2) check whether a goal has been accomplished. Inspired by (Jiang et al., 2019), the goal set generator can be implemented by different approaches, including supervised language models and non-learning-based methods such as human supervisors and functional programs. In our work, we use a non-learning-based method to obtain \mathcal{G}_t and the details are discussed in Sec 5.3 and Appendix B.

After obtaining \mathcal{G}_t , π^{meta} will be used to select a goal $g_t \in \mathcal{G}_t$. We use a graph encoder to encode o_t^{KG} as state representation s_t^{meta} , and a text encoder to encode G_t as a stack of goal representations. Arbitrary graph encoders and text encoders can be used. We implement the graph encoder based on the Relational Graph Convolutional Networks (R-GCNs) (Schlichtkrull et al., 2018) to take both nodes and edges into consideration. For the text encoder, a simple single-block transformer (Vaswani et al., 2017) is sufficient as the goal candidates are short texts. In the goal scorer, we adopt a goal scoring process similar to (He et al., 2016), where s_t^{meta} will be paired with each goal representation, then processed by linear layers to obtain the goal scores. The scores can be treated as either sampling probabilities or Q values, where the goal candidate with the highest Q value will be selected.

Following the Semi-Markov Decision Process (SMDPs) (Sutton et al., 1999), π^{meta} will be reexecuted once a goal is accomplished / failed. π^{meta} receives rewards r_t^{env} from the environment. In a transition for π^{meta} , the reward is set as the sum of environment rewards:

$$r^{\text{meta}} = \sum_{i=1}^{T} r_{t+i}^{\text{env}} \tag{1}$$

where T denotes time steps for accomplishing g_t .

4.3 Sub-policy for action selection

The sub-policy $\pi^{\rm sub}$ follows the goal-conditioned RL setting (Kaelbling, 1993) where a_t is selected by considering both $o_t^{\rm KG}$ and g. Fig. 1 shows the architecture of $\pi^{\rm sub}$ (in blue), which is similar to $\pi^{\rm meta}$ except that the state $s_t^{\rm sub}$ is constructed based on both $o_t^{\rm KG}$ and g. The graph encoder and text encoder in $\pi^{\rm meta}$ can be re-used in $\pi^{\rm sub}$, or be reinitialized with new weights. As this work does not aim at handling the combinatorial action space,

we consider the admissible action set $A_t \subseteq \mathcal{A}$ for each time step. We denote an action as "admissible" if it does not lead to meaningless feedback (e.g., "Nothing happens"). Similar to the goal scorer in π^{meta} , the action scorer will pair s_t^{sub} with each candidate $a_i \in A_t$, followed by linear layers to compute the action scores.

Depending on goal accomplishment, π^{sub} receives binary intrinsic reward $r_t^{\text{goal}} \in \{r_{\min}, r_{\max}\},$ which in this work can be determined by reusing the goal set generator upon $o_{t+1}^{\rm KG}$. Take Fig. 1 as an example. If the goal before observing $o_t^{\rm KG}$ is "find knife", the agent will receive $r_t^{\text{goal}} = r_{\text{max}}$, as this goal is accomplished at time step t. Although the KG can serve as a "map" to provide guidance, such binary reward is insufficient for the agent to accomplish a goal in complex games (e.g., the agent has to go through multiple rooms to find an ingredient). To further improve the performance of π^{sub} , we reshape the sub-reward with the countbased intrinsic reward (Bellemare et al., 2016) to encourage exploration. Specifically, we apply the BeBold method (Zhang et al., 2020) to the textbased games domain. During training, we count the visitation of observations within an episode, and the accumulated visitation throughout the training process. The count-based reward r_t^{count} is then defined as the regulated difference of inverse cumulative visitation counts with episodic restriction:

$$\begin{split} r_{t+1}^{\text{count}} &= \max(\frac{1}{\mathrm{N}_{\mathrm{acc}}(o_t^{\mathrm{KG}})} - \frac{1}{\mathrm{N}_{\mathrm{acc}}(o_{t+1}^{\mathrm{KG}})}, \\ 0) \cdot \mathbb{I}\{\mathrm{N}_{\mathrm{epi}}(o_{t+1}^{\mathrm{KG}}) = 1\} \end{split} \tag{2}$$

where N_{acc} and N_{epi} denote the accumulated and episodic visitation count, respectively. The \mathbb{I} operation returns 1 if o_{t+1}^{KG} is visited for the first time in the current episode, otherwise 0. The reward for $\pi^{\rm sub}$ can then be obtained by combining $r_{t+1}^{\rm goal}$ and $r_{t+1}^{\rm count}$:

$$r_{t+1}^{\text{sub}} = r_{t+1}^{\text{goal}} + \lambda \cdot r_{t+1}^{\text{count}} \tag{3}$$

where λ is a constant coefficient.

4.4 Training H-KGA for multi-task learning

We train H-KGA via Double DQN (Hasselt et al., 2016) with prioritized experience replay (Schaul et al., 2015). Algo. 1 shows the training strategy. We consider a training set $\mathcal{D}_{\text{train}}$ with \mathcal{L} levels of games. For each episode, we sample a game x from $\mathcal{D}_{\text{train}}$ to interact with (lines 2-22). A goal g will be terminated if it is accomplished/ failed, or

Algorithm 1 Training Strategy for H-KGA

```
Input: game sets \{\mathcal{D}_{\text{train}}, \mathcal{D}_{\text{val}}\}, replay buffers \{B^{\text{meta}}, B^{\text{sub}}\},
update frequencies \{F_{\rm up}^{\rm meta}, F_{\rm up}^{\rm sub}\}, validation frequency F_{\rm val},
tolerance \tau, coefficients \beta, \lambda, patience P
Initialize: counters k \leftarrow 1, p \leftarrow 0, N_{\text{acc}} \leftarrow \emptyset, N_{\text{epi}} \leftarrow \emptyset, best
validation score V_{\text{val}} \leftarrow 0, r^{\text{meta}} \leftarrow 0, caches \{C^{\text{meta}}, C^{\text{sub}}\},
policies \{\pi^{\text{meta}}, \pi^{\text{sub}}\}, \{\Pi^{\text{meta}}, \Pi^{\text{sub}}\}
  1: for e \leftarrow 1 to NUM_EPISODES do
                l \leftarrow \text{SampleLevel}(\mathcal{L}, p_l)
                 x \leftarrow \mathsf{SampleGame}(\mathcal{D}_{\mathsf{train}}, l)
  3:
                \begin{array}{l} c_0^{\text{KG}} \leftarrow \text{reset } x \\ C^{\text{meta}} \leftarrow \emptyset, C^{\text{sub}} \leftarrow \emptyset, N_{\text{epi}} \leftarrow \emptyset, \end{array}
  4:
  5:
                \begin{array}{c} \text{Update } N_{\text{acc}}, N_{\text{epi}} \text{ with } o_0^{\text{KG}} \\ \textbf{for } t \leftarrow 0 \text{ to NUM\_STEPS } \textbf{do} \\ g \leftarrow \pi^{\text{meta}}(g|o_t^{\text{KG}}) \\ r^{\text{meta}} \leftarrow 0 \end{array}
  7:
  g.
10:
                          while q is not terminated do
                                  a_t \leftarrow \pi^{\text{sub}}(a|o_t^{\text{KG}},g)
11:
                                  Execute a_t, receive o_{t+1}^{KG}, r_{t+1}^{env}, obtain r_{t+1}^{goal}
12:
13:
                                  Update N_{\text{acc}}, N_{\text{epi}} with o_{t+1}^{\text{KG}}
                                  Compute r_{t+1}^{\text{sub}} using Eq. (2) and Eq. (3)
14:
15:
                                  Store the sub transition into C^{\text{sub}}
                                  r^{\text{meta}} \leftarrow r^{\text{meta}} + r_{t+1}^{\text{env}}
16:
17:
                                  t \leftarrow t + 1
18:
                                  k \leftarrow k+1
                                  if k\%F_{\rm up}^{\rm meta}=0 then
19:
                                          Update(\pi^{\text{meta}}, B^{\text{meta}})
20:
                                  if k\%F_{\rm up}^{\rm sub}=0 then
21:
                                          \operatorname{Update}(\pi^{\operatorname{sub}},B^{\operatorname{sub}})
22:
23:
                          Store the meta transition into C^{\text{meta}}
24:
                  Update p_l using Eq. (4)
                  if \operatorname{Avg}(r^{\text{meta}}|C^{\text{meta}},l) > \tau \cdot \operatorname{Avg}(r^{\text{meta}}|B^{\text{meta}},l) then
25:
                          Store all transitions in C^{\text{meta}} into B^{\text{meta}}
26:
                  if \operatorname{Avg}(r^{\operatorname{goal}}|C^{\operatorname{sub}},l) > \tau \cdot \operatorname{Avg}(r^{\operatorname{goal}}|B^{\operatorname{sub}},l) then
27:
                          Store all transitions in C^{\mathrm{sub}} into B^{\mathrm{sub}}
28:
29:
                  if e\%F_{\rm val}=0 then
30:
                          v_{\text{val}} \leftarrow \text{Validate}(\pi^{\text{meta}}, \pi^{\text{sub}}, \mathcal{D}_{\text{val}})
31:
                          if v_{\text{val}} \geq V_{\text{val}} then
                                  V_{\mathrm{val}} \leftarrow v_{\mathrm{val}}, \, \Pi^{\mathrm{meta}} \leftarrow \pi^{\mathrm{meta}}, \, \Pi^{\mathrm{sub}} \leftarrow \pi^{\mathrm{sub}}
32:
33:
                                  p \leftarrow 0, continue
34:
                          if p > P then
                                 \pi^{\text{meta}} \leftarrow \Pi^{\text{meta}}, \pi^{\text{sub}} \leftarrow \Pi^{\text{sub}}, p \leftarrow 0
35:
36:
37:
                                  p \leftarrow p + 1
```

t exceeds NUM_STEPS. We formulate the meta transition as $\langle o_t^{\rm KG}, g, r^{\rm meta}, o_{t+T}^{\rm KG}, l \rangle$, and the sub transition as $\langle (o_t^{\rm KG}, g), a_t, r_{t+1}^{\rm sub}, r_{t+1}^{\rm goal}, (o_{t+1}^{\rm KG}, g), l \rangle$, where $l \in \mathcal{L}$ denotes the level of a game. We update $\pi^{\rm meta}$ ($\pi^{\rm sub}$) per $F_{\rm up}^{\rm meta}$ ($F_{\rm up}^{\rm sub}$) interaction steps, by sampling a batch of transitions from the replay buffer $B^{\rm meta}$ ($B^{\rm sub}$). In addition, we leverage two strategies empirically effective for previous agents (Adhikari et al., 2020). First, we collect the episodic transitions within a cache, and only push them into the replay buffer when its average reward is greater than τ times the average reward of the buffer (lines 23-26). Second, we validate the model on a validation set $\mathcal{D}_{\rm val}$ per $F_{\rm val}$ episodes and keep track of the best score V and the correspond-

ing policies $\{\Pi^{\text{meta}}, \Pi^{\text{sub}}\}$. We load the training policies $\{\pi^{\text{meta}}, \pi^{\text{sub}}\}$ back to $\{\Pi^{\text{meta}}, \Pi^{\text{sub}}\}$, if the validation performance v_{val} keeps being worse than V for over P times (lines 27-35).

The training process can be formulated as multitask learning if we treat learning on games from the same level as a task. While the knowledge can be shared across levels, different levels may have different scales of training time and performance. For example, those from hard levels generally require more time to learn and tend to have lower normalized performance. To facilitate such multi-task learning setting, we further propose two strategies to improve Algorithm 1: 1) scheduled task sampling and 2) level-aware replay buffer. The scheduled task sampling is inspired by the curriculum learning (Bengio et al., 2009), where we schedule the tasks based on their difficulties. We track the training performance v_l on a level l, and compute the sampling probability as:

$$p_l = \frac{\exp(\beta - v_l)}{\sum_{l_i \in \mathcal{L}} \exp(\beta - v_{l_i})}$$
(4)

where β is a constant coefficient. For each episode, we first sample a level based on the probabilities, and then sample a training game from this level uniformly (lines 2-3). Compared to level-invariant sampling, this strategy encourages the agent to focus more on hard levels with training going on. Another strategy, level-aware replay buffer, is conducted when moving transitions from cache to the replay buffer (lines 23-26). As the transitions collected from hard games tend to have lower reward, they are not likely to be added to the replay buffer. To alleviate this problem, we make the level as an additional component of transition and record the average reward of each level. Then we compare those belonging to the same level to determine whether to add new transitions.

5 Experiments

5.1 Experiment setting

We conduct experiments on multiple levels of cooking games (Côté et al., 2018). While previous work (Adhikari et al., 2020) considered either a single level, or a mixture of 4 levels, we extend their setting to 8 levels. Based on the rl.0.1 game set², we build a training game set \mathcal{D}_{train} with 4 levels, including 100 games per level. We build a

Table 1: Game statistics. "#Ings" denotes the number of ingredients, "#Reqs" denotes the requirements, and "#Acts" denotes the admissible actions per time step.

Level	#Triplets	#Rooms	#Objs	#Ings	#Reqs	#Acts	MaxScore
S1	21.44	1	17.09	1	1	11.54	4
S2	21.50	1	17.49	1	2	11.81	5
S3	46.09	9	34.15	1	0	7.25	3
S4	54.54	6	33.41	3	2	28.38	11
US1	19.85	1	16.01	1	0	7.98	3
US2	20.74	1	16.69	1	1	8.87	4
US3	33.04	6	24.81	1	0	7.61	3
US4	47.31	6	31.09	3	0	13.90	5

validating game set \mathcal{D}_{val} with the same 4 levels of \mathcal{D}_{train} , where each level contains 20 games. We build two testing game sets: $\mathcal{D}_{test}^{seen}$, and $\mathcal{D}_{test}^{unseen}$, both of which contain 4 levels and 20 games per level. The levels within $\mathcal{D}_{test}^{seen}$ have been seen in \mathcal{D}_{train} and \mathcal{D}_{val} , while there is no overlapping game. The levels within $\mathcal{D}_{test}^{unseen}$ are unseen during training. Table 1 shows the game statistics averaged over each level, where "S#" denotes a seen level and "US#" denotes an unseen level.

5.2 Baselines

We consider the following five models, and compare with more variants in ablation studies:

- GATA (Adhikari et al., 2020): a powerful KGbased agent and the state-of-the-art on the rl.0.1 game set. However, it does not have hierarchical architecture, and the action selection policy is not goal-conditioned.
- GC-GATA: GATA equipped with a goal set generator, a goal-conditioned action selection (sub-)policy, and a non-learnable meta-policy for random goal selection.
- H-KGA: the proposed model with both metapolicy and sub-policy.
- H-KGA HalfJoint: an H-KGA variant, where during the first half of training process only the sub-policy is trained, then the two policies are jointly trained.
- H-KGA Ind: an H-KGA variant, where the two policies are individually trained (the subpolicy for the first half, then the meta-policy).

5.3 Implementation details

We implement the models based on GATA's released code³. In particular, we adopt the version

²https://aka.ms/twkg/rl.0.1.zip

³https://github.com/xingdi-eric-yuan/ GATA-public

Table 2: The testing performance at the end of training.

Model	Avg Seen	Avg Unseen	Avg All
GATA	0.47 ± 0.04	0.62 ± 0.07	$0.55{\pm}0.06$
GC-GATA	0.54 ± 0.13	0.61 ± 0.12	$0.58 {\pm} 0.12$
H-KGA (ours)	0.72 ±0.04	0.79 ± 0.04	0.76 ± 0.03
H-KGA HalfJoint	0.56 ± 0.11	0.57 ± 0.07	$0.57 {\pm} 0.09$
H-KGA Ind	0.70 ± 0.02	0.68 ± 0.01	$0.69 {\pm} 0.02$
GATA w/o BeBold	0.54 ± 0.06	0.68 ± 0.02	0.61 ± 0.03
H-KGA w/o BeBold	0.57 ± 0.07	$0.65{\pm}0.09$	$0.61 {\pm} 0.07$
H-KGA w/o Sch	0.52±0.07	0.63 ± 0.07	0.57 ± 0.05
H-KGA w/o Sch w/o LR	0.63 ± 0.14	0.63 ± 0.16	0.63 ± 0.15

GATA-GTF and denote it as GATA for simplicity. GATA-GTF discards textual observations and uses the ground truth full KG as observation, so that there is no information extraction error incurred during KG construction. We design a simple non-learning-based goal set generator to obtain available goals (leaving pre-training-based generators as future work). Please refer to Appendix B for details. All models follow the same architecture of graph encoder (i.e., R-GCNs), text encoder (i.e., single transformer block with single head) and scorers (i.e., linear layers). The encoders in π^{meta} and π^{sub} are initialized separately.

We set the step limit of an episode as 50 for training and 100 for validation / testing. We train the models for 100,000 episodes. All models apply the BeBold reward bonus with $\lambda = 0.1$, and the scheduled sampling method with $\beta = 1.0$. We set B^{meta} with size 50,000 and B^{sub} with size 500,000. We set $F_{\mathrm{up}}^{\mathrm{meta}}$ and $F_{\mathrm{up}}^{\mathrm{sub}}$ as 50 time steps, and the updating starts after 100 episodes with batch size 64. The GC-GATA pre-trained for 50,000 episodes is used for initializing H-KGA HalfJoint and H-KGA Ind. For every 1,000 episodes, we validate the model on \mathcal{D}_{val} , and report the testing performance on $\mathcal{D}_{\text{test}}^{\text{seen}}$ and $\mathcal{D}_{test}^{unseen}$. The experiments are conducted on a Quadro RTX 6000 GPU. Each experiment is run with 3 random seeds, and each run takes 2-3 days to finish.

5.4 Evaluation metrics

We denote a game's score as the episodic sum of rewards without discount. We use the normalized score, which is defined as the collected score normalized by the maximum available score for this game, to measure the performance. For each testing game set, we report the performance on each level and the performance averaged over levels.

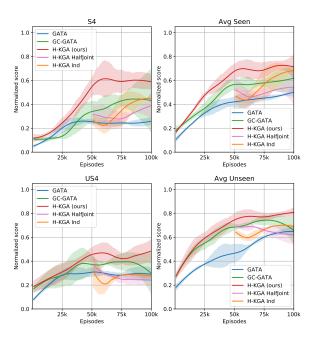


Figure 2: The models' performance on $\mathcal{D}_{test}^{seen}$ ("S4", "Avg Seen") and $\mathcal{D}_{test}^{unseen}$ ("US4", "Avg Unseen").

6 Results and discussions

6.1 Main results

Table 2 shows the testing performance at the end of training, and Fig. 2 shows the models' testing performance with respect to the training episodes. Due to space constraint, we present only results on the two most difficult levels, "S4" and "US4", as well as the average performance on $\mathcal{D}_{test}^{seen}$ and $\mathcal{D}_{test}^{unseen}$ Please refer to Appendix C for the full results. Our H-KGA outperforms baselines in both seen and unseen levels. Its advantage becomes most significant in the most complex level, "S4", which is with the most number of rooms, ingredients and required preparation steps as shown in Table 1. The performance improvement of our model can be attributed to two aspects: the goal-conditioned subpolicy and the meta-policy for adaptive goal selection. GC-GATA, which can be regarded as H-KGA without the meta-policy, also achieves improvement over GATA, demonstrating the effectiveness of goal-conditioned decision making. Compared to GC-GATA, the use of a learned meta-policy helps to further improve H-KGA.

However, we observe that joint training after pretraining the sub-policy leads to performance drop (H-KGA HalfJoint), which could be attributed to the forgetting problem in RL (Vinyals et al., 2019). Another variant, H-KGA Ind, where the pre-trained sub-policy is frozen during training the meta-policy,

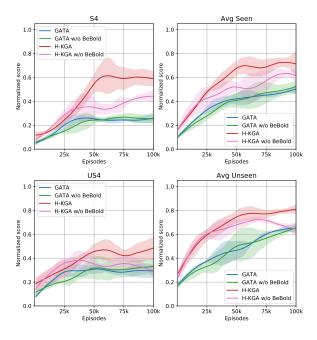


Figure 3: The models' performance with / without the BeBold reward bonus.

performs better and exceeds GC-GATA, but still worse than our H-KGA. While H-KGA Ind might still have space for performance improvement, it requires more training episodes (i.e., collecting more interaction samples), leading to low sample efficiency. Instead, our H-KGA utilizes the training data more efficiently and achieves comparable performance with fewer episodes, making it more favorable for practical applications.

We also observe that learning a good meta-policy helps in solving games from unseen levels. In "US4", where the agent has to navigate through multiple rooms to collect three ingredients, it is more important to learn a strategy to determine the collecting order. In these games, our H-KGA performs better than those without a meta-policy (GATA, GC-GATA), and those with a "not-so-good" meta-policy (H-KGA HalfJoint, H-KGA Ind).

6.2 The influence of exploration

In Sec. 4.3, we enhance the sub-policy with the Be-Bold reward to encourage exploration. We investigate its contribution by comparing models without such rewards. Fig. 3 shows the results. In terms of the average performance, our H-KGA is already better than GATA even without the BeBold reward ("H-KGA w/o BeBold" v.s., "GATA w/o BeBold"). However, the results on "S4" and "US4" show that sufficient exploration is essential for these difficult games, where it's hard for H-KGA without

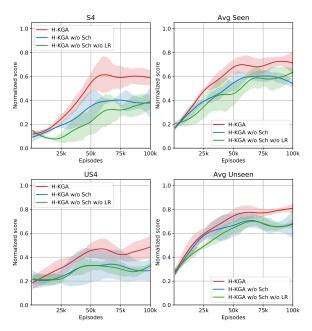


Figure 4: The models' performance with / without the multi-task learning strategies.

BeBold to collect over 50% (40%) of the scores in "S4" ("US4"). We also find that encouraging exploration only is not sufficient, as there is no obvious improvement for GATA, or even worse performance according to Table 2.

6.3 The influence of MTL strategies

In Sec. 4.4, we introduce two strategies to facilitate training H-KGA in the setting of multi-task learning. We then conduct ablation studies to investigate their contributions. Fig. 4 shows the results, where "Sch" denotes the **sch**eduled task sampling and "LR" denotes level-aware replay buffer. Although H-KGA can still achieve comparable average performance in both seen and unseen levels, without scheduled task sampling its performance on difficult levels, which require more training steps to collect more training samples, is limited. Similarly, training without "LR" prevents transitions of difficult levels from being added to the replay buffer, leading to low sample efficiency.

7 Conclusion

In this paper, we investigated generalization for reinforcement learning in text-based games. We introduced a two-level hierarchical framework, H-KGA, to address this problem. In the high level, a meta-policy is executed to decompose the whole game as subtasks characterized by textual goals, and select a goal based on the knowledge graph-based observation. In the low level, a sub-policy is executed to select action conditioned on the goal. Experimental results showed that H-KGA achieved favorable performance on games with various difficulty levels. As an ongoing work, we would like to study automatic goal generation methods. We are also interested in extending our work to more complex scenarios .

Acknowledgement

This work was supported in part by ARC DP180100966 and Facebook Research. We thank Xingdi Yuan and Marc-Alexandre Côté from Microsoft Research, and anonymous reviewers for suggestions.

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The appendix is organized as follows: Sec. A formalizes the text-based games as POMDP. Sec. B details the goal set generator. Sec. C provides more experimental results. Sec. D provides more examples of the observations and the interaction process.

A Text-based games as POMDP

Text-based games can be formulated as Partially Observable Markov Decision Processes (POMDPs), which can be defined as a 7-tuple: $\langle \mathcal{S}, \mathcal{A}, T, R, \Omega, O, \gamma \rangle$, where \mathcal{S} denotes the state set, \mathcal{A} denotes the action set, T denotes the state transition probabilities, R denotes the reward function, Ω denotes the observation set, O denotes the conditional observation probabilities and $\gamma \in (0,1]$ denotes the discount factor. At each time step, the agent will receive an observation $o_t \in \Omega$, depending on the current state and previous action via the conditional observation probability $O(o_t|s_t,a_{t-1})$. By executing an action $a_t \in \mathcal{A}$, the environment will transit into a new state based on the state transition probability $T(s_{t+1}|s_t,a_t)$, and the agent will receive the reward $r_{t+1} = R(s_t,a_t)$. Same as MDPs, the goal of the agent is to learn an optimal policy π^* to maximize the expected future discounted sum of rewards from each time step: $R_t = \mathbb{E}[\sum_{k=0}^{\infty} \gamma^k r_{t+k+1}]$. Instead of using raw textual-based observations, in this work we consider the KG-based observation o_t^{KG} . Besides, we select the action a_t from the admissible action set A_t , which is a subset of A. Both o_t^{KG} and A_t are provided by the environment for each time step.

B Goal set generator

We design a simple non-learning-based goal set generator by exploiting the KG-based observation in the cooking theme. Algorithm 2 shows the pipeline for obtaining the goal set \mathcal{G}_t . We first obtain the ingredient set \mathcal{I} . For each ingredient $i \in \mathcal{I}$, we first check whether it has been collected, then obtain its status set \mathcal{S}_i and requirement set \mathcal{R}_i . We consider three types of goals: 1) "find" requires the agent to find and collect an uncollected ingredient, 2) "prepare" requires the agent to prepare an ingredient to satisfy a requirement, and 3) "eat", that the agent is required to prepare and eat the final meal. Algorithm 3 shows the pipeline for assigning the goal-conditioned reward $r_t^{\rm goal}$. We first obtain the type of a goal g, then check whether this goal has been accomplished given a_t and $o_{t+1}^{\rm KG}$. Some functions in Algorithm 2 can be reused here. $r_t^{\rm goal}$ is a binary reward that we will assign $r_t^{\rm goal} = r_{\rm max}$ if g is accomplished successfully, otherwise $r_{\rm min}$ (still not finished, or failed). Algorithm 2 and Algorithm 3 can also be implemented via learning-based methods. For example, the functions can be achieved by a QA model by answering specific questions.

Algorithm 2 Goal set generation

```
Input: Knowledge graph o_t^{\text{KG}}
Initialize: Goal set \mathcal{G}_t \leftarrow \emptyset
 1: Get ingredient set \mathcal{I} \leftarrow \text{GetIng}(o_t^{\text{KG}})
 2: for each ingredient i \in \mathcal{I} do
3: if CheckCollection(i, o_t^{KG}) = False then
4: Add goal "find i" to \mathcal{G}_t
 5:
              else
 6:
                    Get status set S_i \leftarrow \text{GetStatus}(i, o_t^{\text{KG}})
                    Get requirement set \mathcal{R}_i \leftarrow \text{GetReq}(i, o_t^{\text{KG}})
 7:
                    for each requirement r_i \in \mathcal{R}_i do
 8:
                          if r_i \notin \tilde{\mathcal{S}}_i then
 9:
10:
                                 Add goal "r_i i" to \mathcal{G}_t
11: if G_t = \emptyset then
12:
              Add goal "prepare and eat meal" to \mathcal{G}_t
13: return \mathcal{G}_t.
```

Algorithm 3 Goal-conditioned reward acquisition

```
\overline{	ext{Input: Knowledge graph } o_{t+1}^{	ext{KG}}, 	ext{goal } g, 	ext{rewards } \{r_{	ext{min}}, r_{	ext{max}}\}}
Initialize: FLAG \leftarrow False
 1: Obtain goal type g_{\text{type}} \leftarrow \text{GetGoalType}(g)

2: if g_{\text{type}} = \text{``find''} then

3: Get ingredient i from g

4: if CheckCollection(i, o_{t+1}^{\text{KG}}) = \text{True then}
  5:
                     FLAG \leftarrow True
  6: else if g_{type} = "prepare" then
               Get ingredient i, requirement r from g
Get status set \mathcal{S}_i \leftarrow \text{GetStatus}(i, o_{t+1}^{\text{KG}})
  7:
  8:
  9:
               if r \in \mathcal{S}_i then
10:
                      FLAG \leftarrow True
11: else
               if CheckExistance("meal", o_{t+1}^{\mathrm{KG}}) = True then
12:
                      FLAG \leftarrow True
13:
14: if FLAG = True then
15:
               return r_{\text{max}}.
16: else
17:
               return r_{\min}.
```

C More experiment results

Table. 3, Fig. 5, Fig. 6 and Fig. 7 show the full results in the main paper. Table. 4 shows the maximum testing performance of models throughout the training process. Fig. 8 shows H-KGA's training performance, the sampling probabilities and the proportion of encountered training levels.

Table 3: The testing performance of models at the end of training.

Model	S1	S2	S3	S4	US1	US2	US3	US4	Avg Seen	Avg Unseen	Avg All
GATA	0.70 ± 0.08	0.43 ± 0.02	0.48 ± 0.04	0.28 ± 0.05	0.90 ± 0.04	0.59 ± 0.08	0.71 ± 0.11	0.28 ± 0.09	0.47 ± 0.04	0.62 ± 0.07	0.55±0.06
GC-GATA	0.68 ± 0.18	0.73 ± 0.22	0.43 ± 0.04	0.33 ± 0.23	0.78 ± 0.15	0.79 ± 0.12	0.59 ± 0.11	0.28 ± 0.14	0.54 ± 0.13	0.61 ± 0.12	0.58 ± 0.12
H-KGA (ours)	0.93 ±0.06	$0.85 {\pm} 0.17$	$0.50 {\pm} 0.05$	0.61 ± 0.18	0.97 ± 0.03	0.97 ± 0.03	0.78 ± 0.03	0.44 ± 0.12	0.72±0.04	0.79 ± 0.04	0.76 ± 0.03
H-KGA HalfJoint	0.80 ± 0.12	0.75 ± 0.12	0.43 ± 0.07	0.28 ± 0.11	0.82 ± 0.02	0.81 ± 0.08	0.48 ± 0.16	0.19 ± 0.03	0.56 ± 0.11	0.57 ± 0.07	0.57 ± 0.09
H-KGA Ind	0.91 ± 0.00	0.92 ± 0.04	$0.49 {\pm} 0.02$	0.47 ± 0.04	0.95 ± 0.07	$0.88 {\pm} 0.00$	0.64 ± 0.04	0.27 ± 0.03	0.70 ± 0.02	$0.68 {\pm} 0.01$	0.69 ± 0.02
GATA w/o BeBold	0.78±0.11	0.62 ± 0.13	0.50 ± 0.12	0.24 ± 0.08	0.99±0.02	0.65 ± 0.06	0.73 ± 0.10	0.36 ± 0.07	0.54 ± 0.06	0.68 ± 0.02	0.61 ± 0.03
H-KGA w/o BeBold	0.73±0.14	0.74 ± 0.07	0.43 ± 0.11	0.37 ± 0.09	0.90 ± 0.14	0.77 ± 0.01	0.64 ± 0.10	0.31 ± 0.16	0.57 ± 0.07	0.65 ± 0.09	0.61 ± 0.07
H-KGA w/o Sch	0.73±0.19	0.60 ± 0.16	0.39 ± 0.08	0.34 ± 0.04	0.91 ± 0.01	0.80 ± 0.13	0.52±0.09	0.29 ± 0.07	0.52±0.07	0.63 ± 0.07	0.57±0.05
H-KGA w/o Sch w/o LR	0.85±0.19	0.81 ± 0.14	0.54 ± 0.10	0.33 ± 0.15	0.82 ± 0.23	0.79 ± 0.17	0.60 ± 0.16	0.30 ± 0.10	0.63±0.14	0.63 ± 0.16	0.63 ± 0.15

Table 4: The maximum testing performance of models throughout the training process.

Model	S1	S2	S3	S4	US1	US2	US3	US4	Avg Seen	Avg Unseen	Avg All
GATA	0.83 ± 0.02	0.62 ± 0.06	0.58 ± 0.02	0.34 ± 0.02	0.97 ± 0.03	0.74 ± 0.08	0.82 ± 0.02	0.38 ± 0.03	0.53 ± 0.03	0.67 ± 0.02	0.59 ± 0.02
GC-GATA	0.99 ± 0.01	0.99 ± 0.02	0.52 ± 0.02	0.73 ± 0.13	1.00±0.00	1.00±0.00	0.82 ± 0.03	0.62 ± 0.07	0.76 ± 0.05	0.85 ± 0.02	0.80 ± 0.03
H-KGA (ours)	1.00±0.00	1.00 ± 0.00	0.63 ± 0.06	0.89 ± 0.04	1.00±0.00	1.00 ± 0.00	0.89 ± 0.04	0.65 ± 0.09	0.86 ±0.03	0.88 ± 0.02	0.85 ± 0.02
H-KGA HalfJoint	0.97±0.04	0.99 ± 0.02	0.52 ± 0.01	0.69 ± 0.11	1.00±0.00	1.00 ± 0.00	$0.85{\pm}0.03$	0.61 ± 0.08	0.75±0.04	0.84 ± 0.04	0.78 ± 0.04
H-KGA Ind	0.97±0.04	0.99 ± 0.02	$0.49 {\pm} 0.01$	$0.68 {\pm} 0.11$	1.00±0.00	1.00 ± 0.00	$0.82{\pm}0.06$	$0.58 {\pm} 0.12$	0.72 ± 0.04	$0.81 {\pm} 0.06$	0.75 ± 0.04
GATA w/o BeBold	0.88 ± 0.11	0.71 ± 0.08	0.58 ± 0.05	0.36 ± 0.04	1.00±0.00	0.72 ± 0.06	$0.85{\pm}0.08$	0.50 ± 0.07	0.58 ± 0.05	0.73 ± 0.04	0.63 ± 0.04
H-KGA w/o BeBold	1.00±0.00	0.99 ± 0.01	0.55 ± 0.05	0.72 ± 0.04	1.00±0.00	1.00±0.00	0.82 ± 0.04	0.61 ± 0.05	0.78 ± 0.02	0.80 ± 0.02	0.77 ± 0.02
H-KGA w/o Sch	1.00±0.00	1.00±0.00	0.57 ± 0.06	0.73 ± 0.11	1.00±0.00	1.00±0.00	0.90 ±0.08	0.56 ± 0.15	0.77±0.04	0.84 ± 0.04	0.79 ± 0.03
H-KGA w/o Sch w/o LR	1.00±0.00	1.00 ± 0.00	0.63 ± 0.12	0.67 ± 0.10	1.00±0.00	1.00 ± 0.00	$0.82{\pm}0.05$	0.50 ± 0.05	0.77±0.05	$0.80 {\pm} 0.02$	0.77 ± 0.03

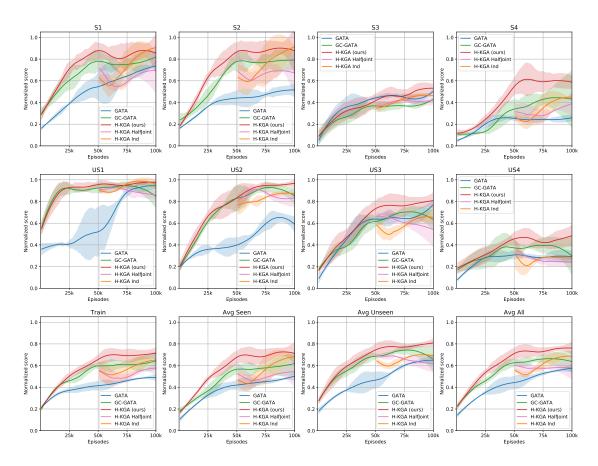


Figure 5: The full results for Sec. 6.1.

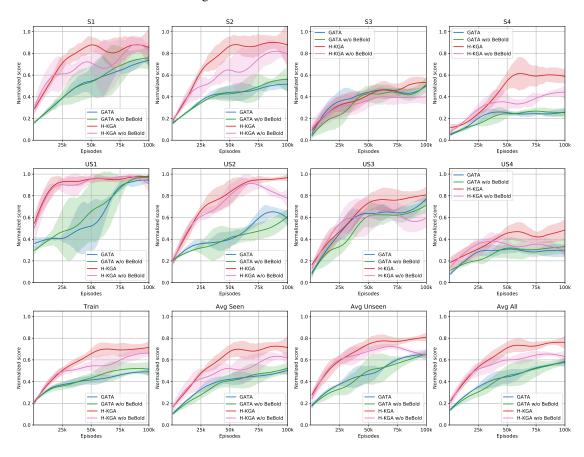


Figure 6: The full results for Sec. 6.2.

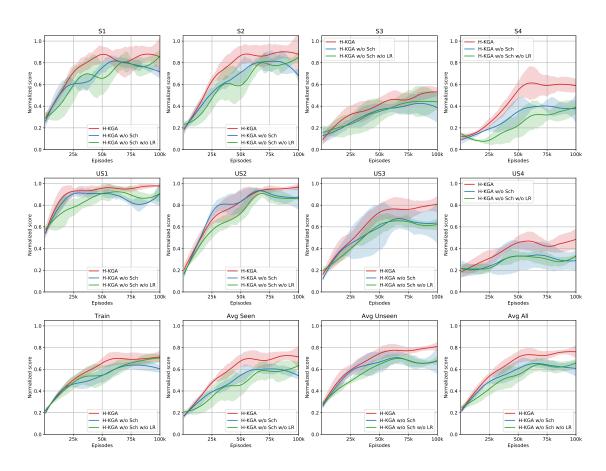


Figure 7: The full results for Sec. 6.3.

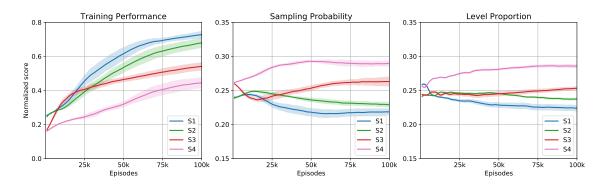


Figure 8: H-KGA's training performance (left), sampling probabilities (middle) and the proportion of training levels (right).

D More game examples

D.1 Observation visualization

We provide more game examples to demonstrate the difference in layouts and difficulty levels. Fig. 9 visualizes the initial observation $o_0^{\rm KG}$ for four games, where "S1 Game1" and "S1 Game2" belong to level "S1", "S2 Game1" and "S2 Game2" belong to level "S2". Fig. 10 visualizes the initial observation of two games belonging to level "S3". Fig. 11 visualizes the initial observation of one game belonging to level "S4". Games within the same level have the same complexity, but are different in their layouts. For example, "S2 Game1" and "S2 Game2" have the same number of rooms, number of ingredients and number of requirements, but the ingredient and requirement are different. Similarly, "S3 Game1" and "S3 Game2" have the same number of rooms, but are with different room connectivity. Games within different levels have different complexities, and their layouts are naturally different (e.g., "S1 Game1" v.s., "S2 Game1" v.s., "S3 Game1" v.s., "S4 Game1"). The TextWorld also provides other game themes, such as the default House theme, the Coin Collector theme and the Treasure Hunter theme. In these themes, the agent needs to go through the rooms to find either the coin, or an object specified at the beginning of an episode. We believe that the Cooking theme we use in this work is able to cover these themes, as it requires the agent to navigate through different numbers of rooms, collect different numbers of ingredients, and prepare them in different ways.

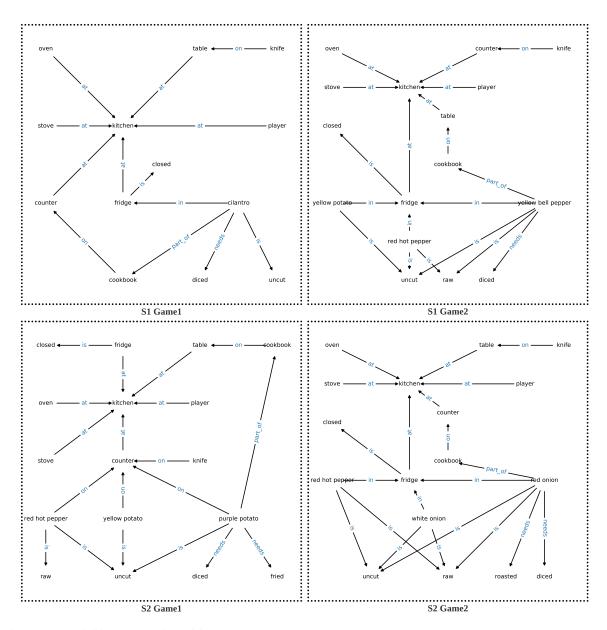
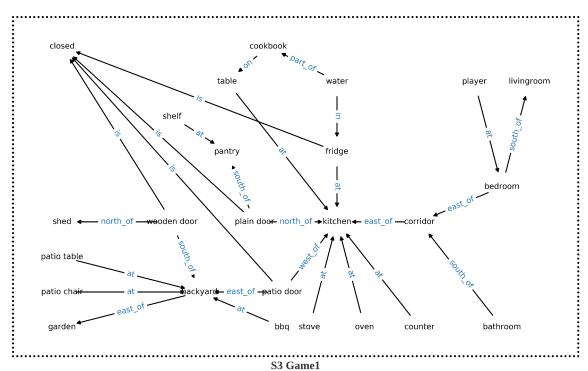


Figure 9: The initial observation of four games, where "S1 Game1" and "S1 Game2" belong to level "S1", "S2 Game1" and "S2 Game2" belong to level "S2".



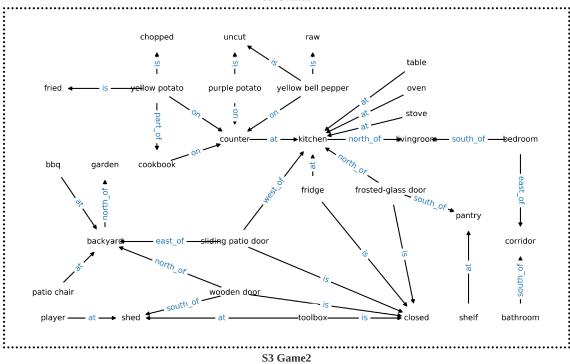


Figure 10: The initial observation of two games belonging to level "S3".

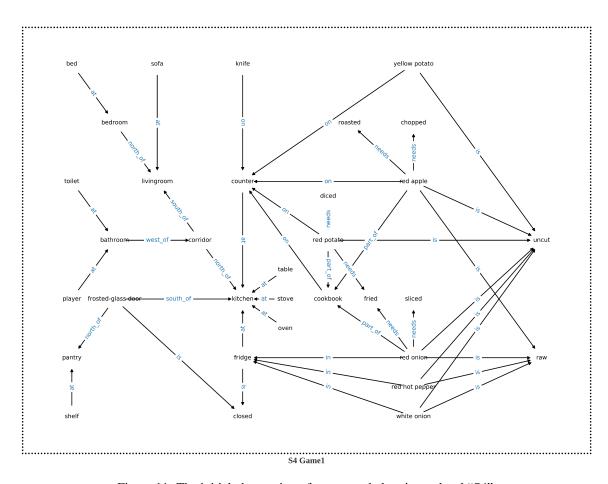


Figure 11: The initial observation of one game belonging to level "S4".

D.2 Interaction

In this section, we show the walk-through interactions of two games: "S1 Game1", which belongs to level "S1", and "S4 Game1", which belongs to level "S4". In "S1 Game1", the player as well as all the objects are in one room ("kitchen"), and there's only one ingredient ("cilantro") and one requirement ("diced"). In "S4 Game1", there are multiple rooms (e.g., "bathroom", "kitchen"), multiple ingredients ("red apple", "red potato" and "red onion"), and multiple requirements (e.g., the red onion needs to be sliced). At each time step, a set of admissible actions are provided, and the player has to select an action from this set. After executing an action, the environment returns the observation for the next time step, the reward, and indicates whether the episode has been terminated ("Done"). If the agent collects an ingredient, or correctly prepares an ingredient, it will receive a positive reward from the environment, otherwise zero. The score denotes the episodic sum of rewards.

D.2.1 S1 Game1

```
===== ---- ===== Step 0 ===== ---- =====
Obs: [['cilantro', 'cookbook', 'part_of'], ['cilantro', 'diced',
   needs'], ['cilantro', 'fridge', 'in'], ['cilantro', 'uncut', 'is'
   ], ['cookbook', 'counter', 'on'], ['counter', 'kitchen', 'at'], ['
   fridge', 'closed', 'is'], ['fridge', 'kitchen', 'at'], ['knife',
   table', 'on'], ['oven', 'kitchen', 'at'], ['player', 'kitchen',
   at'], ['stove', 'kitchen', 'at'], ['table', 'kitchen', 'at']]
Admissible actions: ['examine cookbook', 'open fridge', 'take
   cookbook from counter', 'take knife from table']
Choose: examine cookbook
Reward: 0|Score: 0|Done: False
===== ---- ===== Step 1 ===== ---- =====
Obs: [['cilantro', 'cookbook', 'part_of'], ['cilantro', 'diced', '
   needs'], ['cilantro', 'fridge', 'in'], ['cilantro', 'uncut', 'is'
   ], ['cookbook', 'counter', 'on'], ['counter', 'kitchen', 'at'], ['
   fridge', 'closed', 'is'], ['fridge', 'kitchen', 'at'], ['knife',
   table', 'on'], ['oven', 'kitchen', 'at'], ['player', 'kitchen',
   at'], ['stove', 'kitchen', 'at'], ['table', 'kitchen', 'at']]
Admissible actions: ['examine cookbook', 'open fridge', 'take
   cookbook from counter', 'take knife from table']
Choose: open fridge
Reward: 0|Score: 0|Done: False
==== ---- ==== Step 2 ==== ---- ====
Obs: [['cilantro', 'cookbook', 'part_of'], ['cilantro', 'diced',
   needs'], ['cilantro', 'fridge', 'in'], ['cilantro', 'uncut',
   ], ['cookbook', 'counter', 'on'], ['counter', 'kitchen', 'at'], ['
   fridge', 'kitchen', 'at'], ['fridge', 'open', 'is'], ['knife',
   table', 'on'], ['oven', 'kitchen', 'at'], ['player', 'kitchen', '
   at'], ['stove', 'kitchen', 'at'], ['table', 'kitchen', 'at']]
Admissible actions: ['close fridge', 'examine cookbook', 'take
   cilantro from fridge', 'take cookbook from counter', 'take knife
   from table']
Choose: take cilantro from fridge
Reward: 1|Score: 1|Done: False
===== ---- ===== Step 3 ===== ---- =====
```

```
Obs: [['cilantro', 'cookbook', 'part_of'], ['cilantro', 'diced', '
   needs'], ['cilantro', 'player', 'in'], ['cilantro', 'uncut', 'is'
   ], ['cookbook', 'counter', 'on'], ['counter', 'kitchen', 'at'], ['
   fridge', 'kitchen', 'at'], ['fridge', 'open', 'is'], ['knife',
   table', 'on'], ['oven', 'kitchen', 'at'], ['player', 'kitchen', 'at'], ['stove', 'kitchen', 'at'], ['table', 'kitchen', 'at']]
Admissible actions: ['close fridge', 'cook cilantro with oven', 'cook
    cilantro with stove', 'drop cilantro', 'eat cilantro', 'examine
   cookbook', 'insert cilantro into fridge', 'prepare meal', 'put
   cilantro on counter', 'put cilantro on stove', 'put cilantro on
   table', 'take cookbook from counter', 'take knife from table']
Choose: take knife from table
Reward: 0|Score: 1|Done: False
===== ---- ===== Step 4 ===== ---- =====
Obs: [['cilantro', 'cookbook', 'part_of'], ['cilantro', 'diced', '
   needs'], ['cilantro', 'player', 'in'], ['cilantro', 'uncut', 'is'
   ], ['cookbook', 'counter', 'on'], ['counter', 'kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['fridge', 'open', 'is'], ['knife', '
   player', 'in'], ['oven', 'kitchen', 'at'], ['player', 'kitchen', 'at'], ['stove', 'kitchen', 'at'], ['table', 'kitchen', 'at']]
Admissible actions: ['chop cilantro with knife', 'close fridge', '
   cook cilantro with oven', 'cook cilantro with stove', 'dice
   cilantro with knife', 'drop cilantro', 'drop knife', 'eat cilantro
   ', 'examine cookbook', 'insert cilantro into fridge', 'insert
   knife into fridge', 'prepare meal', 'put cilantro on counter', '
   put cilantro on stove', 'put cilantro on table', 'put knife on
   counter', 'put knife on stove', 'put knife on table', 'slice
   cilantro with knife', 'take cookbook from counter']
Choose: dice cilantro with knife
Reward: 1|Score: 2|Done: False
===== ---- ===== Step 5 ===== ---- =====
Obs: [['cilantro', 'cookbook', 'part_of'], ['cilantro', 'diced', 'is'
   ], ['cilantro', 'diced', 'needs'], ['cilantro', 'player', 'in'], [
   'cookbook', 'counter', 'on'], ['counter', 'kitchen', 'at'], ['
   fridge', 'kitchen', 'at'], ['fridge', 'open', 'is'], ['knife', '
           'in'], ['oven', 'kitchen', 'at'], ['player', 'kitchen', '
   at'], ['stove', 'kitchen', 'at'], ['table', 'kitchen', 'at']]
Admissible actions: ['close fridge', 'cook cilantro with oven', 'cook
    cilantro with stove', 'drop cilantro', 'drop knife', 'eat
   cilantro', 'examine cookbook', 'insert cilantro into fridge', '
   insert knife into fridge', 'prepare meal', 'put cilantro on
   counter', 'put cilantro on stove', 'put cilantro on table', 'put
   knife on counter', 'put knife on stove', 'put knife on table', '
   take cookbook from counter']
Choose: drop knife
Reward: 0|Score: 2|Done: False
==== ---- ==== Step 6 ===== ---- =====
```

```
Obs: [['cilantro', 'cookbook', 'part_of'], ['cilantro', 'diced', 'is'
   ], ['cilantro', 'diced', 'needs'], ['cilantro', 'player', 'in'], [
   'cookbook', 'counter', 'on'], ['counter', 'kitchen', 'at'], ['
   fridge', 'kitchen', 'at'], ['fridge', 'open', 'is'], ['knife', 'kitchen', 'at'], ['oven', 'kitchen', 'at'], ['player', 'kitchen', 'at'], ['stove', 'kitchen', 'at'], ['table', 'kitchen', 'at']]
Admissible actions: ['close fridge', 'cook cilantro with oven', 'cook
    cilantro with stove', 'drop cilantro', 'eat cilantro', 'examine
   cookbook', 'insert cilantro into fridge', 'prepare meal', 'put
   cilantro on counter', 'put cilantro on stove', 'put cilantro on
   table', 'take cookbook from counter', 'take knife']
Choose: prepare meal
Reward: 1|Score: 3|Done: False
===== ---- ===== Step 7 ===== ---- =====
Obs: [['cilantro', 'cookbook', 'part_of'], ['cilantro', 'diced', 'is'
   ], ['cilantro', 'diced', 'needs'], ['cookbook', 'counter', 'on'],
   ['counter', 'kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['
   fridge', 'open', 'is'], ['knife', 'kitchen', 'at'], ['meal',
   player', 'in'], ['meal', 'raw', 'is'], ['oven', 'kitchen', 'at'],
   ['player', 'kitchen', 'at'], ['stove', 'kitchen', 'at'], ['table',
     'kitchen', 'at']]
Admissible actions: ['close fridge', 'cook meal with oven', 'cook
   meal with stove', 'drop meal', 'eat meal', 'examine cookbook', '
   insert meal into fridge', 'put meal on counter', 'put meal on
   stove', 'put meal on table', 'take cookbook from counter', 'take
   knife']
Choose: eat meal
Reward: 1|Score: 4|Done: True
Final obs: [['cilantro', 'cookbook', 'part_of'], ['cilantro', 'diced'
   , 'is'], ['cilantro', 'diced', 'needs'], ['cookbook', 'counter', '
   on'], ['counter', 'kitchen', 'at'], ['fridge', 'kitchen', 'at'], [
'fridge', 'open', 'is'], ['knife', 'kitchen', 'at'], ['meal', '
consumed', 'is'], ['meal', 'raw', 'is'], ['oven', 'kitchen', 'at'
   ], ['player', 'kitchen', 'at'], ['stove', 'kitchen', 'at'], ['
   table', 'kitchen', 'at']]
```

D.2.2 S4 Game1

```
===== ---- ==== Step 0 ==== ---- =====
Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'],
    ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on
'], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', '
    north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', '
    kitchen', 'at'], ['fridge', 'closed', 'is'], ['fridge', 'kitchen',
    'at'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass
    door', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', '
    north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', '
    counter', 'on'], ['livingroom', 'bedroom', 'south_of'], ['
    livingroom', 'corridor', 'north_of'], ['oven', 'kitchen', 'at'], ['
```

'player', 'bathroom', 'at'], ['red apple', 'chopped', 'needs'], ['red apple', 'cookbook', 'part_of'], ['red apple', 'counter', 'on'], ['red apple', 'raw', 'is'], ['red apple', 'roasted', 'needs'], ['red apple', 'uncut', 'is'], ['red hot pepper', 'fridge', 'in'], ['red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', 'is'], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fridge', 'in'], ['red onion', 'fried', 'needs'], ['red onion', 'raw', 'is'], ['red onion', 'sliced', 'needs'], ['red onion', 'uncut', 'is'], ['red potato', 'cookbook', 'part_of'], ['red potato', 'counter', 'on'], ['red potato', 'diced', 'needs'], ['red potato', 'fried', 'needs'], ['red potato', 'uncut', 'is'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], ['stove', 'kitchen', 'at'], ['table', 'kitchen', 'at'], ['toilet', 'bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion', 'raw', 'is'], ['white onion', 'uncut', 'is'], ['yellow potato', 'counter', 'on'], ['yellow potato', 'uncut', 'is']]

Admissible actions: ['go east']

Choose: go east

Reward: 0|Score: 0|Done: False

===== ---- ===== Step 1 ===== ---- =====

Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'], ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', ' north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', kitchen', 'at'], ['fridge', 'closed', 'is'], ['fridge', 'kitchen', 'at'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', ' north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', ' counter', 'on'], ['livingroom', 'bedroom', 'south_of'], [' livingroom', 'corridor', 'north_of'], ['oven', 'kitchen', 'at'], ['player', 'corridor', 'at'], ['red apple', 'chopped', 'needs'], [' red apple', 'cookbook', 'part_of'], ['red apple', 'counter', 'on'], ['red apple', 'raw', 'is'], ['red apple', 'roasted', 'needs'], ['red apple', 'uncut', 'is'], ['red hot pepper', 'fridge', 'in'], ['red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', 'is'], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fridge', ' in'], ['red onion', 'fried', 'needs'], ['red onion', 'raw', 'is'], ['red onion', 'sliced', 'needs'], ['red onion', 'uncut', 'is'], [
'red potato', 'cookbook', 'part_of'], ['red potato', 'counter', ' on'], ['red potato', 'diced', 'needs'], ['red potato', 'fried', ' needs'], ['red potato', 'uncut', 'is'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], ['stove', 'kitchen', 'at'], ['table ', 'kitchen', 'at'], ['toilet', 'bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion', 'raw', 'is'], ['white onion', ' uncut', 'is'], ['yellow potato', 'counter', 'on'], ['yellow potato ', 'uncut', 'is']]

Admissible actions: ['go north', 'go south', 'go west']

Choose: go south

Reward: 0|Score: 0|Done: False

```
===== ---- ===== Step 2 ===== ---- =====
Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'],
   ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on
   '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen',
   north_of'], ['corridor', 'livingroom', 'south_of'], ['counter',
   kitchen', 'at'], ['fridge', 'closed', 'is'], ['fridge', 'kitchen',
    'at'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass
   door', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', '
   north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', '
   counter', 'on'], ['livingroom', 'bedroom', 'south_of'], ['
   livingroom', 'corridor', 'north_of'], ['oven', 'kitchen', 'at'], [
   'player', 'kitchen', 'at'], ['red apple', 'chopped', 'needs'], ['
   red apple', 'cookbook', 'part_of'], ['red apple', 'counter', 'on'
   ], ['red apple', 'raw', 'is'], ['red apple', 'roasted', 'needs'],
   ['red apple', 'uncut', 'is'], ['red hot pepper', 'fridge', 'in'],
   ['red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', 'is'
   ], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fridge', '
   in'], ['red onion', 'fried', 'needs'], ['red onion', 'raw', 'is'],
    ['red onion', 'sliced', 'needs'], ['red onion', 'uncut', 'is'], [
   'red potato', 'cookbook', 'part_of'], ['red potato', 'counter',
   on'], ['red potato', 'diced', 'needs'], ['red potato', 'fried', '
   needs'], ['red potato', 'uncut', 'is'], ['shelf', 'pantry', 'at'],
    ['sofa', 'livingroom', 'at'], ['stove', 'kitchen', 'at'], ['table
   ', 'kitchen', 'at'], ['toilet', 'bathroom', 'at'], ['white onion',
    'fridge', 'in'], ['white onion', 'raw', 'is'], ['white onion', '
   uncut', 'is'], ['yellow potato', 'counter', 'on'], ['yellow potato
   ', 'uncut', 'is']]
Admissible actions: ['examine cookbook', 'go north', 'open fridge', '
   open frosted-glass door', 'take cookbook from counter', 'take
   knife from counter', 'take red apple from counter', 'take red
   potato from counter', 'take yellow potato from counter']
Choose: examine cookbook
Reward: 0|Score: 0|Done: False
===== ---- ===== Step 3 ===== ---- =====
Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'],
   ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on
   '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen',
   north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', '
kitchen', 'at'], ['fridge', 'closed', 'is'], ['fridge', 'kitchen',
    'at'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass
   door', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', '
   north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', '
   counter', 'on'], ['livingroom', 'bedroom', 'south_of'], ['
   livingroom', 'corridor', 'north_of'], ['oven', 'kitchen', 'at'], [
   'player', 'kitchen', 'at'], ['red apple', 'chopped', 'needs'], ['
   red apple', 'cookbook', 'part_of'], ['red apple', 'counter', 'on'], ['red apple', 'raw', 'is'], ['red apple', 'roasted', 'needs'], ['red apple', 'uncut', 'is'], ['red hot pepper', 'fridge', 'in'],
   ['red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', 'is'
   ], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fridge', '
```

in'], ['red onion', 'fried', 'needs'], ['red onion', 'raw', 'is'], ['red onion', 'sliced', 'needs'], ['red onion', 'uncut', 'is'], ['red potato', 'cookbook', 'part_of'], ['red potato', 'counter', on'], ['red potato', 'diced', 'needs'], ['red potato', 'fried', needs'], ['red potato', 'uncut', 'is'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], ['stove', 'kitchen', 'at'], ['table ', 'kitchen', 'at'], ['toilet', 'bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion', 'raw', 'is'], ['white onion', 'uncut', 'is'], ['yellow potato', 'counter', 'on'], ['yellow potato ', 'uncut', 'is']] Admissible actions: ['examine cookbook', 'go north', 'open fridge', ' open frosted-glass door', 'take cookbook from counter', 'take knife from counter', 'take red apple from counter', 'take red potato from counter', 'take yellow potato from counter'] Choose: take red apple from counter Reward: 1|Score: 1|Done: False ===== ---- ===== Step 4 ===== ---- ===== Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'], ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', '
kitchen', 'at'], ['fridge', 'closed', 'is'], ['fridge', 'kitchen', 'at'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', ' north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', ' counter', 'on'], ['livingroom', 'bedroom', 'south_of'], [livingroom', 'corridor', 'north_of'], ['oven', 'kitchen', 'at'], ['player', 'kitchen', 'at'], ['red apple', 'chopped', 'needs'], [' red apple', 'cookbook', 'part_of'], ['red apple', 'player', 'in'], ['red apple', 'raw', 'is'], ['red apple', 'roasted', 'needs'], [' red apple', 'uncut', 'is'], ['red hot pepper', 'fridge', 'in'], [' red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', 'is'], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fridge', 'in'], ['red onion', 'fried', 'needs'], ['red onion', 'raw', 'is'], [' red onion', 'sliced', 'needs'], ['red onion', 'uncut', 'is'], ['

', 'uncut', 'is']]
Admissible actions: ['cook red apple with oven', 'cook red apple with stove', 'drop red apple', 'eat red apple', 'examine cookbook', 'go north', 'open fridge', 'open frosted-glass door', 'prepare meal', 'put red apple on counter', 'put red apple on stove', 'put red apple on table', 'take cookbook from counter', 'take knife from counter', 'take red potato from counter', 'take yellow potato from counter']

red potato', 'cookbook', 'part_of'], ['red potato', 'counter', 'on '], ['red potato', 'diced', 'needs'], ['red potato', 'fried', '

needs'], ['red potato', 'uncut', 'is'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], ['stove', 'kitchen', 'at'], ['table

', 'kitchen', 'at'], ['toilet', 'bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion', 'raw', 'is'], ['white onion', 'uncut', 'is'], ['yellow potato', 'counter', 'on'], ['yellow potato

Choose: open fridge

Reward: 0|Score: 1|Done: False

===== ---- ===== Step 5 ===== ---- =====

Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'], ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', ' north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['fridge', 'open', ' is'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door ', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', ' north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', counter', 'on'], ['livingroom', 'bedroom', 'south_of'], [livingroom', 'corridor', 'north_of'], ['oven', 'kitchen', 'at'], ['player', 'kitchen', 'at'], ['red apple', 'chopped', 'needs'], [' red apple', 'cookbook', 'part_of'], ['red apple', 'player', 'in'], ['red apple', 'raw', 'is'], ['red apple', 'roasted', 'needs'], [' red apple', 'uncut', 'is'], ['red hot pepper', 'fridge', 'in'], [' red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', 'is'], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fridge', 'in'], ['red onion', 'fried', 'needs'], ['red onion', 'raw', 'is'], [' red onion', 'sliced', 'needs'], ['red onion', 'uncut', 'is'], [' red potato', 'cookbook', 'part_of'], ['red potato', 'counter', 'on '], ['red potato', 'diced', 'needs'], ['red potato', 'fried', needs'], ['red potato', 'uncut', 'is'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], ['stove', 'kitchen', 'at'], ['table ', 'kitchen', 'at'], ['toilet', 'bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion', 'raw', 'is'], ['white onion', ' uncut', 'is'], ['yellow potato', 'counter', 'on'], ['yellow potato ', 'uncut', 'is']]

Admissible actions: ['close fridge', 'cook red apple with oven', 'cook red apple with stove', 'drop red apple', 'eat red apple', 'examine cookbook', 'go north', 'insert red apple into fridge', 'open frosted-glass door', 'prepare meal', 'put red apple on counter', 'put red apple on stove', 'put red apple on table', 'take cookbook from counter', 'take knife from counter', 'take red hot pepper from fridge', 'take red onion from fridge', 'take red potato from counter', 'take white onion from fridge', 'take yellow potato from counter']

Choose: take red onion from fridge Reward: 1|Score: 2|Done: False

==== ---- ==== Step 6 ===== ---- =====

Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'], ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', 'north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', 'kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['fridge', 'open', 'is'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', 'north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', '

counter', 'on'], ['livingroom', 'bedroom', 'south_of'], ['
livingroom', 'corridor', 'north_of'], ['oven', 'kitchen', 'at'], [
'player', 'kitchen', 'at'], ['red apple', 'chopped', 'needs'], ['
red apple', 'cookbook', 'part_of'], ['red apple', 'player', 'in'],
 ['red apple', 'raw', 'is'], ['red apple', 'roasted', 'needs'], ['
red apple', 'uncut', 'is'], ['red hot pepper', 'fridge', 'in'], ['
red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', 'is'],
 ['red onion', 'cookbook', 'part_of'], ['red onion', 'raw', 'is'],
 ['red onion', 'sliced', 'needs'], ['red onion', 'uncut', 'is'],
 ['red potato', 'cookbook', 'part_of'], ['red potato', 'counter',
'on'], ['red potato', 'diced', 'needs'], ['red potato', 'fried', '
needs'], ['red potato', 'uncut', 'is'], ['shelf', 'pantry', 'at'],
 ['sofa', 'livingroom', 'at'], ['stove', 'kitchen', 'at'], ['table', 'kitchen', 'at'], ['toilet', 'bathroom', 'at'], ['white onion', 'uncut', 'is'], ['white onion', 'uncut', 'is'], ['white onion', 'uncut', 'is'], ['yellow potato', 'counter', 'on'], ['yellow potato', 'uncut', 'is'], ['yellow potato', 'uncut', 'is']]

Admissible actions: ['close fridge', 'cook red apple with oven', 'cook red apple with stove', 'cook red onion with oven', 'cook red onion with stove', 'drop red apple', 'drop red onion', 'eat red apple', 'eat red onion', 'examine cookbook', 'go north', 'insert red apple into fridge', 'insert red onion into fridge', 'open frosted-glass door', 'prepare meal', 'put red apple on counter', 'put red apple on stove', 'put red apple on table', 'put red onion on counter', 'put red onion on stove', 'put red onion on table', 'take cookbook from counter', 'take knife from counter', 'take red hot pepper from fridge', 'take red potato from counter', 'take white onion from fridge', 'take yellow potato from counter']

Choose: take red potato from counter

Reward: 1|Score: 3|Done: False

===== ---- ===== Step 7 ===== ---- =====

Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'], ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', ' north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['fridge', 'open', ' is'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', ' north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', counter', 'on'], ['livingroom', 'bedroom', 'south_of'], [livingroom', 'corridor', 'north_of'], ['oven', 'kitchen', 'at'], ['player', 'kitchen', 'at'], ['red apple', 'chopped', 'needs'], [' red apple', 'cookbook', 'part_of'], ['red apple', 'player', 'in'], ['red apple', 'raw', 'is'], ['red apple', 'roasted', 'needs'], [' red apple', 'uncut', 'is'], ['red hot pepper', 'fridge', 'in'], [' red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', 'is'], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fried', ' needs'], ['red onion', 'player', 'in'], ['red onion', 'raw',], ['red onion', 'sliced', 'needs'], ['red onion', 'uncut', 'is'],

['red potato', 'cookbook', 'part_of'], ['red potato', 'diced', 'needs'], ['red potato', 'fried', 'needs'], ['red potato', 'player', 'in'], ['red potato', 'uncut', 'is'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], ['stove', 'kitchen', 'at'], ['table', 'kitchen', 'at'], ['toilet', 'bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion', 'raw', 'is'], ['white onion', 'uncut', 'is'], ['yellow potato', 'counter', 'on'], ['yellow potato', 'uncut', 'is']]

Admissible actions: ['close fridge', 'cook red apple with oven', 'cook red apple with stove', 'cook red onion with oven', 'cook red onion with stove', 'drop red apple', 'drop red onion', 'drop red potato with stove', 'drop red apple', 'examine cookbook', 'go north', 'insert red apple into fridge', 'insert red onion into fridge', 'insert red potato into fridge', 'open frosted-glass door', 'prepare meal', 'put red apple on counter', 'put red apple on stove', 'put red apple on table', 'put red onion on counter', 'put red onion on stove', 'put red potato on counter', 'put red potato on counter', 'take knife from counter', 'take red hot pepper from fridge', 'take white onion from fridge', 'take yellow potato from counter']

Choose: cook red apple with oven Reward: 1|Score: 4|Done: False

==== ---- ==== Step 8 ==== ---- ====

Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'], ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', ' north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', '
kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['fridge', 'open', ' is'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door ', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', counter', 'on'], ['livingroom', 'bedroom', 'south_of'], [' livingroom', 'corridor', 'north_of'], ['oven', 'kitchen', 'at'], ['player', 'kitchen', 'at'], ['red apple', 'chopped', 'needs'], [' red apple', 'cookbook', 'part_of'], ['red apple', 'player', 'in'], ['red apple', 'roasted', 'is'], ['red apple', 'roasted', 'needs'], ['red apple', 'uncut', 'is'], ['red hot pepper', 'fridge', 'in'], ['red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', ' is'], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fried', 'needs'], ['red onion', 'player', 'in'], ['red onion', 'raw', 'is '], ['red onion', 'sliced', 'needs'], ['red onion', 'uncut', 'is'], ['red potato', 'cookbook', 'part_of'], ['red potato', 'diced', 'needs'], ['red potato', 'fried', 'needs'], ['red potato', 'player', 'in'], ['red potato', 'uncut', 'is'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], ['stove', 'kitchen', 'at'], [' table', 'kitchen', 'at'], ['toilet', 'bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion', 'raw', 'is'], ['white onion', 'uncut', 'is'], ['yellow potato', 'counter', 'on'], ['

yellow potato', 'uncut', 'is']]

Admissible actions: ['close fridge', 'cook red apple with oven', 'cook red onion with stove', 'cook red potato with oven', 'cook red potato with stove', 'drop red apple', 'drop red onion', 'drop red potato', 'eat red apple', 'eat red onion', 'examine cookbook', 'go north', 'insert red apple into fridge', 'insert red onion into fridge', 'insert red potato into fridge', 'open frosted-glass door', 'prepare meal', 'put red apple on counter', 'put red apple on stove', 'put red apple on table', 'put red onion on counter', 'put red onion on stove', 'put red potato on counter', 'put red potato on counter', 'put red potato on from counter', 'take knife from counter', 'take red hot pepper from fridge', 'take white onion from fridge', 'take yellow potato from counter']

Choose: cook red onion with stove Reward: 1|Score: 5|Done: False

===== ---- ===== Step 9 ===== ---- =====

Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'], ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', ' north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['fridge', 'open', ' is'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door ', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', ' north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', ' counter', 'on'], ['livingroom', 'bedroom', 'south_of'], [livingroom', 'corridor', 'north_of'], ['oven', 'kitchen', 'at'], ['player', 'kitchen', 'at'], ['red apple', 'chopped', 'needs'], [' red apple', 'cookbook', 'part_of'], ['red apple', 'player', 'in'], ['red apple', 'roasted', 'is'], ['red apple', 'roasted', 'needs'], ['red apple', 'uncut', 'is'], ['red hot pepper', 'fridge', 'in'], ['red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', ' is'], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fried', 'is'], ['red onion', 'fried', 'needs'], ['red onion', 'player', ' in'], ['red onion', 'sliced', 'needs'], ['red onion', 'uncut', 'is
'], ['red potato', 'cookbook', 'part_of'], ['red potato', 'diced', 'needs'], ['red potato', 'fried', 'needs'], ['red potato', ' player', 'in'], ['red potato', 'uncut', 'is'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], ['stove', 'kitchen', 'at'], ['table', 'kitchen', 'at'], ['toilet', 'bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion', 'raw', 'is'], ['white onion', 'uncut', 'is'], ['yellow potato', 'counter', 'on'], [' yellow potato', 'uncut', 'is']]

Admissible actions: ['close fridge', 'cook red apple with oven', 'cook red apple with stove', 'cook red onion with oven', 'cook red onion with stove', 'cook red potato with oven', 'cook red potato with stove', 'drop red apple', 'drop red onion', 'drop red potato', 'eat red apple', 'eat red onion', 'examine cookbook', 'go north', 'insert red apple into fridge', 'insert red onion into fridge',

'insert red potato into fridge', 'open frosted-glass door', '
prepare meal', 'put red apple on counter', 'put red apple on stove
', 'put red apple on table', 'put red onion on counter', 'put red
onion on stove', 'put red onion on table', 'put red potato on
counter', 'put red potato on stove', 'put red potato on table', '
take cookbook from counter', 'take knife from counter', 'take red
hot pepper from fridge', 'take white onion from fridge', 'take
yellow potato from counter']

Choose: cook red potato with stove

Reward: 1|Score: 6|Done: False

===== ---- ===== Step 10 ===== ---- =====

Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'], ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', 'north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', 'kitchen', 'at'], ['fridge', 'open', ' is'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door ', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', counter', 'on'], ['livingroom', 'bedroom', 'south_of'], [' livingroom', 'corridor', 'north_of'], ['oven', 'kitchen', 'at'], ['player', 'kitchen', 'at'], ['red apple', 'chopped', 'needs'], [' red apple', 'cookbook', 'part_of'], ['red apple', 'player', 'in'], ['red apple', 'roasted', 'is'], ['red apple', 'roasted', 'needs'], ['red apple', 'uncut', 'is'], ['red hot pepper', 'fridge', 'in'], ['red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', ' is'], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fried',
'is'], ['red onion', 'fried', 'needs'], ['red onion', 'player', ' in'], ['red onion', 'sliced', 'needs'], ['red onion', 'uncut', 'is '], ['red potato', 'cookbook', 'part_of'], ['red potato', 'diced', 'needs'], ['red potato', 'fried', 'is'], ['red potato', 'fried', 'needs'], ['red potato', 'player', 'in'], ['red potato', 'uncut', 'is'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], ['stove', 'kitchen', 'at'], ['table', 'kitchen', 'at'], ['toilet', ' bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion', 'raw', 'is'], ['white onion', 'uncut', 'is'], ['yellow potato', counter', 'on'], ['yellow potato', 'uncut', 'is']] Admissible actions: ['close fridge', 'cook red apple with oven', ' cook red apple with stove', 'cook red onion with oven', 'cook red onion with stove', 'cook red potato with oven', 'cook red potato with stove', 'drop red apple', 'drop red onion', 'drop red potato' , 'eat red apple', 'eat red onion', 'eat red potato', 'examine cookbook', 'go north', 'insert red apple into fridge', 'insert red onion into fridge', 'insert red potato into fridge', 'open frosted-glass door', 'prepare meal', 'put red apple on counter', ' put red apple on stove', 'put red apple on table', 'put red onion on counter', 'put red onion on stove', 'put red onion on table', ' put red potato on counter', 'put red potato on stove', 'put red potato on table', 'take cookbook from counter', 'take knife from counter', 'take red hot pepper from fridge', 'take white onion

from fridge', 'take yellow potato from counter'] Choose: take knife from counter Reward: 0|Score: 6|Done: False ===== ---- ===== Step 11 ===== ---- ===== Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'], ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen' north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['fridge', 'open', 'is'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door ', 'kitchen', 'south of'], ['frosted-glass door', 'pantry', ' north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', 'player
', 'in'], ['livingroom', 'bedroom', 'south_of'], ['livingroom', ' corridor', 'north_of'], ['oven', 'kitchen', 'at'], ['player', '
kitchen', 'at'], ['red apple', 'chopped', 'needs'], ['red apple', 'cookbook', 'part_of'], ['red apple', 'player', 'in'], ['red apple ', 'roasted', 'is'], ['red apple', 'roasted', 'needs'], ['red apple', 'uncut', 'is'], ['red hot pepper', 'fridge', 'in'], ['red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', 'is'], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fried', 'is'], ['red onion', 'fried', 'needs'], ['red onion', 'player', 'in'], ['red onion', 'sliced', 'needs'], ['red onion', 'uncut', 'is'], [' red potato', 'cookbook', 'part_of'], ['red potato', 'diced', needs'], ['red potato', 'fried', 'is'], ['red potato', 'fried', 'needs'], ['red potato', 'player', 'in'], ['red potato', 'uncut', ' is'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], [' stove', 'kitchen', 'at'], ['table', 'kitchen', 'at'], ['toilet', bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion', 'raw', 'is'], ['white onion', 'uncut', 'is'], ['yellow potato', counter', 'on'], ['yellow potato', 'uncut', 'is']] Admissible actions: ['chop red apple with knife', 'chop red onion with knife', 'chop red potato with knife', 'close fridge', 'cook red apple with oven', 'cook red apple with stove', 'cook red onion with oven', 'cook red onion with stove', 'cook red potato with oven', 'cook red potato with stove', 'dice red apple with knife', 'dice red onion with knife', 'dice red potato with knife', 'drop knife', 'drop red apple', 'drop red onion', 'drop red potato', eat red apple', 'eat red onion', 'eat red potato', 'examine cookbook', 'go north', 'insert knife into fridge', 'insert red apple into fridge', 'insert red onion into fridge', 'insert red potato into fridge', 'open frosted-glass door', 'prepare meal', ' put knife on counter', 'put knife on stove', 'put knife on table', 'put red apple on counter', 'put red apple on stove', 'put red apple on table', 'put red onion on counter', 'put red onion on stove', 'put red onion on table', 'put red potato on counter', ' put red potato on stove', 'put red potato on table', 'slice red apple with knife', 'slice red onion with knife', 'slice red potato with knife', 'take cookbook from counter', 'take red hot pepper from fridge', 'take white onion from fridge', 'take yellow potato from counter']

Choose: chop red apple with knife Reward: 1|Score: 7|Done: False

===== ---- ===== Step 12 ===== ---- =====

Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'], ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', ' north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['fridge', 'open', ' is'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door ', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', ' north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', 'player ', 'in'], ['livingroom', 'bedroom', 'south_of'], ['livingroom', corridor', 'north_of'], ['oven', 'kitchen', 'at'], ['player', kitchen', 'at'], ['red apple', 'chopped', 'is'], ['red apple', ' chopped', 'needs'], ['red apple', 'cookbook', 'part_of'], ['red apple', 'player', 'in'], ['red apple', 'roasted', 'is'], ['red apple', 'roasted', 'needs'], ['red hot pepper', 'fridge', 'in'], [
'red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', 'is'], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fried', 'is'], ['red onion', 'fried', 'needs'], ['red onion', 'player', 'in'], ['red onion', 'sliced', 'needs'], ['red onion', 'uncut', 'is'], ['red potato', 'cookbook', 'part_of'], ['red potato', 'diced', ' needs'], ['red potato', 'fried', 'is'], ['red potato', 'fried', 'needs'], ['red potato', 'player', 'in'], ['red potato', 'uncut', 'is'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], [' stove', 'kitchen', 'at'], ['table', 'kitchen', 'at'], ['toilet', bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion', 'raw', 'is'], ['white onion', 'uncut', 'is'], ['yellow potato', counter', 'on'], ['yellow potato', 'uncut', 'is']] Admissible actions: ['chop red onion with knife', 'chop red potato with knife', 'close fridge', 'cook red apple with oven', 'cook red apple with stove', 'cook red onion with oven', 'cook red onion with stove', 'cook red potato with oven', 'cook red potato with stove', 'dice red onion with knife', 'dice red potato with knife', 'drop knife', 'drop red apple', 'drop red onion', 'drop red potato', 'eat red apple', 'eat red onion', 'eat red potato', ' examine cookbook', 'go north', 'insert knife into fridge', 'insert red apple into fridge', 'insert red onion into fridge', 'insert red potato into fridge', 'open frosted-glass door', 'prepare meal' , 'put knife on counter', 'put knife on stove', 'put knife on table', 'put red apple on counter', 'put red apple on stove', 'put red apple on table', 'put red onion on counter', 'put red onion on stove', 'put red onion on table', 'put red potato on counter', 'put red potato on stove', 'put red potato on table', 'slice red onion with knife', 'slice red potato with knife', 'take cookbook from counter', 'take red hot pepper from fridge', 'take white onion from fridge', 'take yellow potato from counter']

Choose: drop knife

Reward: 0|Score: 7|Done: False

```
===== ---- ===== Step 13 ===== ---- =====
Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'],
    ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on
    '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen',
   north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', '
kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['fridge', 'open', '
is'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door'
    ', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry',
    north_of'], ['kitchen', 'corridor', 'south_of'], ['knife',
    kitchen', 'at'], ['livingroom', 'bedroom', 'south_of'], ['
    livingroom', 'corridor', 'north_of'], ['oven', 'kitchen', 'at'], [
    'player', 'kitchen', 'at'], ['red apple', 'chopped', 'is'], ['red
   apple', 'chopped', 'needs'], ['red apple', 'cookbook', 'part_of'],
     ['red apple', 'player', 'in'], ['red apple', 'roasted', 'is'], ['
   red apple', 'roasted', 'needs'], ['red hot pepper', 'fridge', 'in'], ['red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', '
   is'], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fried', 'is'], ['red onion', 'fried', 'needs'], ['red onion', 'player', 'in'], ['red onion', 'sliced', 'needs'], ['red onion', 'uncut', 'is'], ['red potato', 'cookbook', 'part_of'], ['red potato', 'diced',
    'needs'], ['red potato', 'fried', 'is'], ['red potato', 'fried', 'needs'], ['red potato', 'player', 'in'], ['red potato', 'uncut',
    'is'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], ['
    stove', 'kitchen', 'at'], ['table', 'kitchen', 'at'], ['toilet', '
   bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion',
     'raw', 'is'], ['white onion', 'uncut', 'is'], ['yellow potato',
counter', 'on'], ['yellow potato', 'uncut', 'is']]
Admissible actions: ['close fridge', 'cook red apple with oven', '
    cook red apple with stove', 'cook red onion with oven', 'cook red
    onion with stove', 'cook red potato with oven', 'cook red potato
    with stove', 'drop red apple', 'drop red onion', 'drop red potato'
    , 'eat red apple', 'eat red onion', 'eat red potato', 'examine
   cookbook', 'go north', 'insert red apple into fridge', 'insert red
     onion into fridge', 'insert red potato into fridge', 'open
   frosted-glass door', 'prepare meal', 'put red apple on counter', '
    put red apple on stove', 'put red apple on table', 'put red onion
   on counter', 'put red onion on stove', 'put red onion on table', '
    put red potato on counter', 'put red potato on stove', 'put red
    potato on table', 'take cookbook from counter', 'take knife', '
    take red hot pepper from fridge', 'take white onion from fridge',
    'take yellow potato from counter']
Choose: take knife
Reward: 0|Score: 7|Done: False
===== ---- ===== Step 14 ===== ---- =====
Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'],
    ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on
    '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', '
   north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', '
kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['fridge', 'open', '
is'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door'
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', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', '
   north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', 'player
   ', 'in'], ['livingroom', 'bedroom', 'south_of'], ['livingroom',
   corridor', 'north_of'], ['oven', 'kitchen', 'at'], ['player',
   kitchen', 'at'], ['red apple', 'chopped', 'is'], ['red apple', '
   chopped', 'needs'], ['red apple', 'cookbook', 'part_of'], ['red
   apple', 'player', 'in'], ['red apple', 'roasted', 'is'], ['red
   apple', 'roasted', 'needs'], ['red hot pepper', 'fridge', 'in'], [
'red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', 'is'],
   ['red onion', 'cookbook', 'part_of'], ['red onion', 'fried', 'is'], ['red onion', 'fried', 'needs'], ['red onion', 'player', 'in'], ['red onion', 'sliced', 'needs'], ['red onion', 'uncut', 'is'], [
   'red potato', 'cookbook', 'part_of'], ['red potato', 'diced', '
   needs'], ['red potato', 'fried', 'is'], ['red potato', 'fried', '
   needs'], ['red potato', 'player', 'in'], ['red potato', 'uncut', is'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], ['
   stove', 'kitchen', 'at'], ['table', 'kitchen', 'at'], ['toilet', '
   bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion',
     'raw', 'is'], ['white onion', 'uncut', 'is'], ['yellow potato',
   counter', 'on'], ['yellow potato', 'uncut', 'is']]
Admissible actions: ['chop red onion with knife', 'chop red potato
   with knife', 'close fridge', 'cook red apple with oven', 'cook red
     apple with stove', 'cook red onion with oven', 'cook red onion
   with stove', 'cook red potato with oven', 'cook red potato with
   stove', 'dice red onion with knife', 'dice red potato with knife',
    'drop knife', 'drop red apple', 'drop red onion', 'drop red
   potato', 'eat red apple', 'eat red onion', 'eat red potato', '
   examine cookbook', 'go north', 'insert knife into fridge', 'insert
    red apple into fridge', 'insert red onion into fridge', 'insert
   red potato into fridge', 'open frosted-glass door', 'prepare meal', 'put knife on counter', 'put knife on stove', 'put knife on
   table', 'put red apple on counter', 'put red apple on stove', 'put
    red apple on table', 'put red onion on counter', 'put red onion
   on stove', 'put red onion on table', 'put red potato on counter',
   'put red potato on stove', 'put red potato on table', 'slice red
   onion with knife', 'slice red potato with knife', 'take cookbook
   from counter', 'take red hot pepper from fridge', 'take white
   onion from fridge', 'take yellow potato from counter']
Choose: slice red onion with knife
Reward: 1|Score: 8|Done: False
===== ---- ===== Step 15 ===== ---- =====
Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'],
   ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on
   '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', '
   north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', '
   kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['fridge', 'open', 'is'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door'
   ', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', '
   north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', 'player
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', 'in'], ['livingroom', 'bedroom', 'south_of'], ['livingroom', '

corridor', 'north_of'], ['oven', 'kitchen', 'at'], ['player', ' kitchen', 'at'], ['red apple', 'chopped', 'is'], ['red apple', ' chopped', 'needs'], ['red apple', 'cookbook', 'part_of'], ['red apple', 'player', 'in'], ['red apple', 'roasted', 'is'], ['red apple', 'roasted', 'needs'], ['red hot pepper', 'fridge', 'in'], [
'red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', 'is'], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fried', 'is'], ['red onion', 'fried', 'needs'], ['red onion', 'player', 'in'], ['red onion', 'sliced', 'is'], ['red onion', 'sliced', 'needs'], ['red potato', 'cookbook', 'part_of'], ['red potato', 'diced', 'needs'], ['red potato', 'fried', 'is'], ['red potato', 'fried', ' needs'], ['red potato', 'player', 'in'], ['red potato', 'uncut', ' is'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], [' stove', 'kitchen', 'at'], ['table', 'kitchen', 'at'], ['toilet', ' bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion', 'raw', 'is'], ['white onion', 'uncut', 'is'], ['yellow potato', counter', 'on'], ['yellow potato', 'uncut', 'is']] Admissible actions: ['chop red potato with knife', 'close fridge', ' cook red apple with oven', 'cook red apple with stove', 'cook red onion with oven', 'cook red onion with stove', 'cook red potato with oven', 'cook red potato with stove', 'dice red potato with knife', 'drop knife', 'drop red apple', 'drop red onion', 'drop red potato', 'eat red apple', 'eat red onion', 'eat red potato', ' examine cookbook', 'go north', 'insert knife into fridge', 'insert red apple into fridge', 'insert red onion into fridge', 'insert red potato into fridge', 'open frosted-glass door', 'prepare meal' , 'put knife on counter', 'put knife on stove', 'put knife on table', 'put red apple on counter', 'put red apple on stove', 'put red apple on table', 'put red onion on counter', 'put red onion on stove', 'put red onion on table', 'put red potato on counter', 'put red potato on stove', 'put red potato on table', 'slice red potato with knife', 'take cookbook from counter', 'take red hot pepper from fridge', 'take white onion from fridge', 'take yellow potato from counter'] Choose: drop knife

Reward: 0|Score: 8|Done: False

===== ---- ===== Step 16 ===== ---- =====

Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'], ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', ' north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', ' kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['fridge', 'open', ' is'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door ', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', ' north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', kitchen', 'at'], ['livingroom', 'bedroom', 'south_of'], [livingroom', 'corridor', 'north_of'], ['oven', 'kitchen', 'at'], ['player', 'kitchen', 'at'], ['red apple', 'chopped', 'is'], ['red apple', 'chopped', 'needs'], ['red apple', 'cookbook', 'part_of'], ['red apple', 'player', 'in'], ['red apple', 'roasted', 'is'], ['

red apple', 'roasted', 'needs'], ['red hot pepper', 'fridge', 'in'], ['red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', 'is'], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fried', 'is'], ['red onion', 'fried', 'needs'], ['red onion', 'player', 'in'], ['red onion', 'sliced', 'is'], ['red onion', 'sliced', 'needs'], ['red potato', 'cookbook', 'part_of'], ['red potato', 'diced', 'needs'], ['red potato', 'fried', 'is'], ['red potato', 'fried', 'needs'], ['red potato', 'player', 'in'], ['red potato', 'uncut', 'is'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], ['stove', 'kitchen', 'at'], ['table', 'kitchen', 'at'], ['toilet', 'bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion', 'uncut', 'is'], ['yellow potato', 'uncut', 'is'], ['yellow potato', 'uncut', 'is']]

Admissible actions: ['close fridge', 'cook red apple with oven', 'cook red apple with stove', 'cook red onion with oven', 'cook red onion with stove', 'drop red apple', 'drop red onion', 'drop red potato with stove', 'drop red apple', 'eat red onion', 'eat red potato', 'eat red apple', 'eat red onion', 'eat red potato', 'examine cookbook', 'go north', 'insert red apple into fridge', 'insert red onion into fridge', 'insert red potato into fridge', 'open frosted-glass door', 'prepare meal', 'put red apple on counter', 'put red apple on stove', 'put red apple on table', 'put red onion on counter', 'put red onion on stove', 'put red onion on table', 'take cookbook from counter', 'take knife', 'take red hot pepper from fridge', 'take white onion from fridge', 'take yellow potato from counter']

Choose: take knife

Reward: 0|Score: 8|Done: False

===== ---- ===== Step 17 ===== ---- =====

Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'], ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on'], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', ' north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['fridge', 'open', 'is'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door ', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', ' north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', 'player ', 'in'], ['livingroom', 'bedroom', 'south_of'], ['livingroom', corridor', 'north_of'], ['oven', 'kitchen', 'at'], ['player', kitchen', 'at'], ['red apple', 'chopped', 'is'], ['red apple', chopped', 'needs'], ['red apple', 'cookbook', 'part_of'], ['red apple', 'player', 'in'], ['red apple', 'roasted', 'is'], ['red apple', 'roasted', 'needs'], ['red hot pepper', 'fridge', 'in'], ['red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', 'is'], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fried', 'is'], ['red onion', 'fried', 'needs'], ['red onion', 'player', 'in'], ['red onion', 'sliced', 'is'], ['red onion', 'sliced', 'needs'], ['red potato', 'cookbook', 'part_of'], ['red potato', 'diced', '

needs'], ['red potato', 'fried', 'is'], ['red potato', 'fried', ' needs'], ['red potato', 'player', 'in'], ['red potato', 'uncut', ' is'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], [' stove', 'kitchen', 'at'], ['table', 'kitchen', 'at'], ['toilet', ' bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion', 'raw', 'is'], ['white onion', 'uncut', 'is'], ['yellow potato', counter', 'on'], ['yellow potato', 'uncut', 'is']] Admissible actions: ['chop red potato with knife', 'close fridge', ' cook red apple with oven', 'cook red apple with stove', 'cook red onion with oven', 'cook red onion with stove', 'cook red potato with oven', 'cook red potato with stove', 'dice red potato with knife', 'drop knife', 'drop red apple', 'drop red onion', 'drop red potato', 'eat red apple', 'eat red onion', 'eat red potato', ' examine cookbook', 'go north', 'insert knife into fridge', 'insert red apple into fridge', 'insert red onion into fridge', 'insert red potato into fridge', 'open frosted-glass door', 'prepare meal' , 'put knife on counter', 'put knife on stove', 'put knife on table', 'put red apple on counter', 'put red apple on stove', 'put red apple on table', 'put red onion on counter', 'put red onion on stove', 'put red onion on table', 'put red potato on counter', 'put red potato on stove', 'put red potato on table', 'slice red potato with knife', 'take cookbook from counter', 'take red hot pepper from fridge', 'take white onion from fridge', 'take yellow potato from counter']

Choose: dice red potato with knife Reward: 1|Score: 9|Done: False

===== ---- ===== Step 18 ===== ---- =====

Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'], ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', ' north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['fridge', 'open', 'is'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door' ', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', ' north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', 'player ', 'in'], ['livingroom', 'bedroom', 'south_of'], ['livingroom', corridor', 'north_of'], ['oven', 'kitchen', 'at'], ['player', kitchen', 'at'], ['red apple', 'chopped', 'is'], ['red apple', ' chopped', 'needs'], ['red apple', 'cookbook', 'part_of'], ['red apple', 'player', 'in'], ['red apple', 'roasted', 'is'], ['red apple', 'roasted', 'needs'], ['red hot pepper', 'fridge', 'in'], [
'red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', 'is'], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fried', 'is'], ['red onion', 'fried', 'needs'], ['red onion', 'player', 'in'], ['red onion', 'sliced', 'is'], ['red onion', 'sliced', 'needs'], ['red potato', 'cookbook', 'part_of'], ['red potato', 'diced', 'is '], ['red potato', 'diced', 'needs'], ['red potato', 'fried', 'is'], ['red potato', 'fried', 'needs'], ['red potato', 'player', 'in'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], [' stove', 'kitchen', 'at'], ['table', 'kitchen', 'at'], ['toilet', '

bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion', 'raw', 'is'], ['white onion', 'uncut', 'is'], ['yellow potato', ' counter', 'on'], ['yellow potato', 'uncut', 'is']] Admissible actions: ['close fridge', 'cook red apple with oven', ' cook red apple with stove', 'cook red onion with oven', 'cook red onion with stove', 'cook red potato with oven', 'cook red potato with stove', 'drop knife', 'drop red apple', 'drop red onion', ' drop red potato', 'eat red apple', 'eat red onion', 'eat red potato', 'examine cookbook', 'go north', 'insert knife into fridge , 'insert red apple into fridge', 'insert red onion into fridge', 'insert red potato into fridge', 'open frosted-glass door', ' prepare meal', 'put knife on counter', 'put knife on stove', 'put knife on table', 'put red apple on counter', 'put red apple on stove', 'put red apple on table', 'put red onion on counter', 'put red onion on stove', 'put red onion on table', 'put red potato on counter', 'put red potato on stove', 'put red potato on table', ' take cookbook from counter', 'take red hot pepper from fridge', ' take white onion from fridge', 'take yellow potato from counter']

Choose: drop knife

Reward: 0|Score: 9|Done: False

===== ---- ===== Step 19 ===== ---- =====

Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'], ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', ' north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', '
kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['fridge', 'open', ' is'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door ', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', ' north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', kitchen', 'at'], ['livingroom', 'bedroom', 'south_of'], [' livingroom', 'corridor', 'north_of'], ['oven', 'kitchen', 'at'], ['player', 'kitchen', 'at'], ['red apple', 'chopped', 'is'], ['red apple', 'chopped', 'needs'], ['red apple', 'cookbook', 'part_of'],
 ['red apple', 'player', 'in'], ['red apple', 'roasted', 'is'], [' red apple', 'roasted', 'needs'], ['red hot pepper', 'fridge', 'in'], ['red hot pepper', 'raw', 'is'], ['red hot pepper', 'uncut', ' is'], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fried',
 'is'], ['red onion', 'fried', 'needs'], ['red onion', 'player',
in'], ['red onion', 'sliced', 'is'], ['red onion', 'sliced',' needs'], ['red potato', 'cookbook', 'part_of'], ['red potato', ' diced', 'is'], ['red potato', 'diced', 'needs'], ['red potato', fried', 'is'], ['red potato', 'fried', 'needs'], ['red potato', player', 'in'], ['shelf', 'pantry', 'at'], ['sofa', 'livingroom', 'at'], ['stove', 'kitchen', 'at'], ['table', 'kitchen', 'at'], [' toilet', 'bathroom', 'at'], ['white onion', 'fridge', 'in'], [' white onion', 'raw', 'is'], ['white onion', 'uncut', 'is'], [' yellow potato', 'counter', 'on'], ['yellow potato', 'uncut', 'is'

Admissible actions: ['close fridge', 'cook red apple with oven', 'cook red apple with stove', 'cook red onion with oven', 'cook red

onion with stove', 'cook red potato with oven', 'cook red potato with stove', 'drop red apple', 'drop red onion', 'drop red potato', 'eat red apple', 'eat red onion', 'eat red potato', 'examine cookbook', 'go north', 'insert red apple into fridge', 'insert red onion into fridge', 'insert red potato into fridge', 'open frosted-glass door', 'prepare meal', 'put red apple on counter', 'put red apple on stove', 'put red apple on table', 'put red onion on counter', 'put red onion on stove', 'put red onion on stove', 'put red potato on stove', 'put red potato on table', 'take cookbook from counter', 'take knife', 'take red hot pepper from fridge', 'take white onion from fridge', 'take yellow potato from counter']

Choose: prepare meal

Reward: 1|Score: 10|Done: False

===== ----- ===== Step 20 ===== ----- =====

Obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'], ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter', 'on '], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', ' north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', '
kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['fridge', 'open', '
is'], ['frosted-glass door', 'closed', 'is'], ['frosted-glass door' ', 'kitchen', 'south_of'], ['frosted-glass door', 'pantry', ' north_of'], ['kitchen', 'corridor', 'south_of'], ['knife', kitchen', 'at'], ['livingroom', 'bedroom', 'south_of'], [' livingroom', 'corridor', 'north_of'], ['meal', 'player', 'in'], [' meal', 'raw', 'is'], ['oven', 'kitchen', 'at'], ['player', 'kitchen', 'at'], ['red apple', 'chopped', 'is'], ['red apple', ' chopped', 'needs'], ['red apple', 'cookbook', 'part_of'], ['red apple', 'roasted', 'is'], ['red apple', 'roasted', 'needs'], ['red hot pepper', 'fridge', 'in'], ['red hot pepper', 'raw', 'is'], [' red hot pepper', 'uncut', 'is'], ['red onion', 'cookbook', '
part_of'], ['red onion', 'fried', 'is'], ['red onion', 'fried', '
needs'], ['red onion', 'sliced', 'is'], ['red onion', 'sliced', '
needs'], ['red potato', 'cookbook', 'part_of'], ['red potato', ' diced', 'is'], ['red potato', 'diced', 'needs'], ['red potato', ' fried', 'is'], ['red potato', 'fried', 'needs'], ['shelf', 'pantry ', 'at'], ['sofa', 'livingroom', 'at'], ['stove', 'kitchen', 'at'], ['table', 'kitchen', 'at'], ['toilet', 'bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion', 'raw', 'is'], ['white onion', 'uncut', 'is'], ['yellow potato', 'counter', 'on'], ['yellow potato', 'uncut', 'is']]

Admissible actions: ['close fridge', 'cook meal with oven', 'cook meal with stove', 'drop meal', 'eat meal', 'examine cookbook', 'go north', 'insert meal into fridge', 'open frosted-glass door', 'put meal on counter', 'put meal on stove', 'put meal on table', 'take cookbook from counter', 'take knife', 'take red hot pepper from fridge', 'take white onion from fridge', 'take yellow potato from counter']

Choose: eat meal

Reward: 1|Score: 11|Done: True

===== ---- ===== ---- =====

Final obs: [['bathroom', 'corridor', 'west_of'], ['bed', 'bedroom', 'at'], ['bedroom', 'livingroom', 'north_of'], ['cookbook', 'counter ', 'on'], ['corridor', 'bathroom', 'east_of'], ['corridor', 'kitchen', 'north_of'], ['corridor', 'livingroom', 'south_of'], ['counter', 'kitchen', 'at'], ['fridge', 'kitchen', 'at'], ['fridge' , 'open', 'is'], ['frosted-glass door', 'closed', 'is'], ['frosted -glass door', 'kitchen', 'south_of'], ['frosted-glass door', ' pantry', 'north_of'], ['kitchen', 'corridor', 'south_of'], ['knife
', 'kitchen', 'at'], ['livingroom', 'bedroom', 'south_of'], ['
livingroom', 'corridor', 'north_of'], ['meal', 'consumed', 'is'], ['meal', 'raw', 'is'], ['oven', 'kitchen', 'at'], ['player', ' kitchen', 'at'], ['red apple', 'chopped', 'is'], ['red apple', ' chopped', 'needs'], ['red apple', 'cookbook', 'part_of'], ['red apple', 'roasted', 'is'], ['red apple', 'roasted', 'needs'], ['red hot pepper', 'fridge', 'in'], ['red hot pepper', 'raw', 'is'], [' red hot pepper', 'uncut', 'is'], ['red onion', 'cookbook', 'part_of'], ['red onion', 'fried', 'is'], ['red onion', 'fried', needs'], ['red onion', 'sliced', 'is'], ['red onion', 'sliced',
needs'], ['red potato', 'cookbook', 'part_of'], ['red potato', ' diced', 'is'], ['red potato', 'diced', 'needs'], ['red potato', ' fried', 'is'], ['red potato', 'fried', 'needs'], ['shelf', 'pantry ', 'at'], ['sofa', 'livingroom', 'at'], ['stove', 'kitchen', 'at'], ['table', 'kitchen', 'at'], ['toilet', 'bathroom', 'at'], ['white onion', 'fridge', 'in'], ['white onion', 'raw', 'is'], ['white onion', 'uncut', 'is'], ['yellow potato', 'counter', 'on'], ['yellow potato', 'uncut', 'is']]