KnowledgeBot: Improving Assistive Robot for Task Completion and Live Interaction via Neuro-Symbolic Reasoning

Minqian Liu Ying Shen Barry Menglong Yao Sijia Wang
Jingyuan Qi Zhiyang Xu Lifu Huang

Department of Computer Science
Virginia Tech

{minqianliu, yings, barryyao, sijiawang, jingyq1, zhiyangx, lifuh}@vt.edu

Abstract

As artificial intelligence continues to advance, the development of intelligent assistive agents that can help people in completing daily tasks has become an area of increasing interest. However, the automation of such agents presents several challenges: (1) the enormous variety of user-defined tasks, (2) the ability of complex reasoning and visual comprehension for carrying out actions, and (3) natural interaction with humans. In this paper, we introduce KnowledgeBot, a conversational embodied agent designed to address these challenges. KnowledgeBot is designed for the Alexa Prize SimBot Challenge. The primary goal of this agent is to accomplish various tasks effectively by interacting with users while ensuring an optimal user experience. To achieve this, KnowledgeBot processes user instructions and environmental perceptions correspondingly take actions and respond to users through a series of components, including symbolic reasoning and neural-based action planning and prediction modules, vision models for semantic segmentation and visual grounding, as well as a situated dialogue module. By integrating these components, our agent is capable of carrying out a variety of tasks interactively with users in a natural and conversational manner. We demonstrate the effectiveness of our approach by evaluating our approach on TEACh and Arena instruction following datasets.

1 Introduction

With the rapid advancement of artificial intelligence (AI), there is an increasing interest in the development of intelligent assistive agents, which have the capability to assist individuals to finish their daily tasks. One promising research direction is the creation of assistive robots that can operate in various environments and perform various tasks. Assistive robots can perform various tasks in everyday environments and have the potential to greatly improve the quality of life for individuals, particularly the elderly or those with disabilities.

Automating assistive robots presents numerous challenges in multiple aspects. **First,** the tasks users require assistance with are diverse and can range from basic activities such as making a toast to more complex ones like combing hair, making it challenging to acquire knowledge for such extensive activities. **Second,** the robot must employ complex reasoning and visual understanding to determine the proper sequence of actions. This involves accurately interpreting the scene from the environment in real-time, determining the actions to perform based on the target goal and the current state, monitoring state changes of objects after executing actions, and predicting and verifying if the

1st Alexa Prize Simbot Challenge.

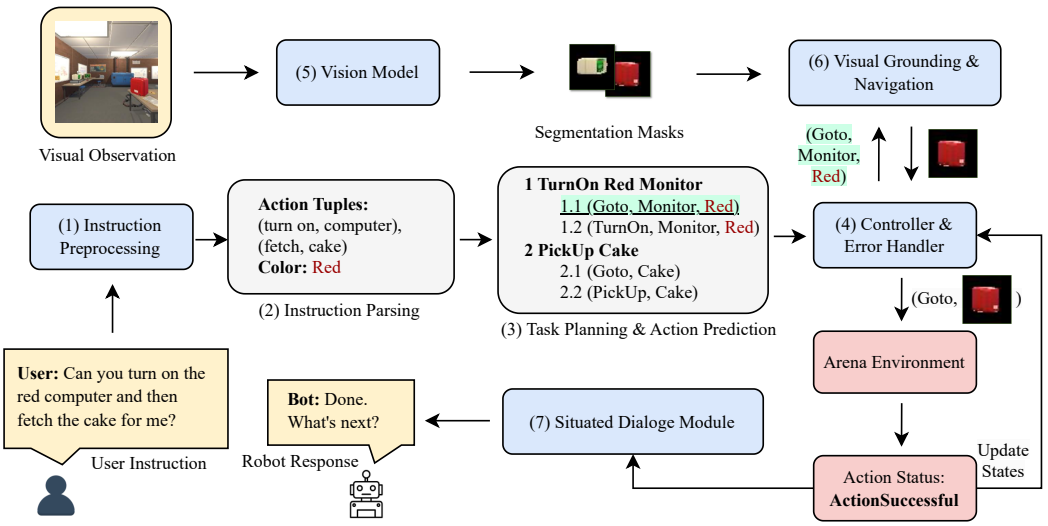


Figure 1: **System overview.**

actions have been executed successfully or if it's the time to move on. **Third,** the robot must actively engage and interact with the user by asking questions or presenting alternatives to address ambiguity or confusion while performing tasks. Accomplishing this requires generating appropriate questions and interpreting human instructions and feedback accordingly.

To address these challenges, we propose KnowledgeBot, a conversational embodied agent that can understand user instructions, perceive the environment, and complete various tasks within a game-like environment through natural and engaging interactions with users. To address the **first** challenge, we propose incorporating both symbolic reasoning and neural-based action planning into the prediction modules to break down complicated user instructions and utilize pre-trained language models to construct sequences of sub-goals for task completion. For the **second** challenge of complex reasoning and visual grounding, we propose a Visual Grounding and a Viewpoint-based Navigation module. The Visual Grounding module utilizes both Area Grounding and Color Grounding methods to identify the object mask that best matches the objects in the given instruction. This approach enables the agent to accurately identify and locate objects within a complex visual environment. Additionally, the Viewpoint-based Navigation module facilitates the agent's movement toward the desired location by analyzing the panoramic view from various viewpoints and determining if the target object is present within each view. This approach provides the agent with an effective means of navigating toward specific objects within a complex visual environment. To tackle the **third** challenge, to enhance user interaction while performing tasks, we present a Situated Dialogue Module that employs template-based methods to generate responses tailored to each unique case. Moreover, we design a Controller and Error Handler that integrates the separate modules into a cohesive system and helps to improve user experience by handling potential exceptions that could occur in various components.

We evaluate the performance of our KnowledgeBot in various task scenarios in TEACh [33] and Arena [10] instruction following benchmarks, showcasing its capability to effectively engage with users and complete tasks seamlessly and naturally.

2 System Overview

Problem Formulation Our high-level goal is to build an intelligent agent for completing various daily tasks. We first introduce the notion of *session* where a user interacts with the agent in a game aiming to complete a certain goal (e.g., repair the broken bowl with a time machine). In one session, the agent is required to take in the **user instructions** sequentially and acquire the **environment perceptions** (e.g., egocentric views and the states of previously executed actions). While there is an explicit goal in each game, the ultimate objectives of the agent are two-fold: (1) completing the goal with a minimal cost (i.e., with the least number of steps), and (2) maximizing the user experience (UX) during the game.

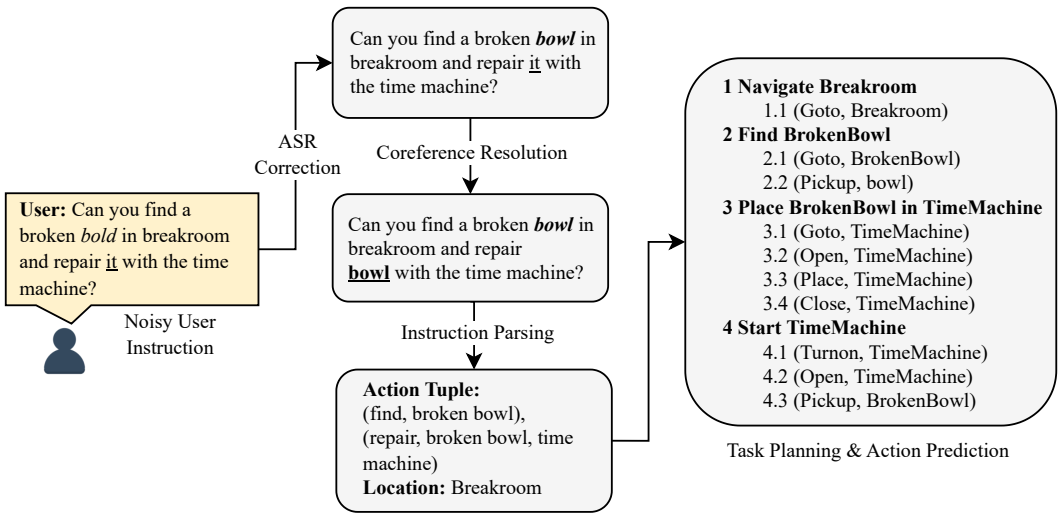


Figure 2: **Illustration of instruction processing and understanding.**

System Workflow We present the overall workflow of our system in Figure 2. Given the user instruction and visual observation from the environment as inputs, we first (1) preprocess and (2) parse the instruction into a more structured format. Step (1) and (2) consists of an ASR correction component, a co-reference resolution component, and an instruction parser based on dependency parsing. We then (3) predict a list of more fine-grained and atomic actions via either a symbolic reasoning program or a neural-based action planning and prediction module. Next, we (4) feed the action list into the controller and start to process each action in the list one by one. Meanwhile, we (5) use a vision model to produce a set of semantic segmentation masks from the visual observation. If the controller is processing an action that either performs navigation or requires returning an object mask, then we further (6) apply a visual grounding & navigation module to either navigate the agent to a certain viewpoint or ground the action with a desired object mask. Finally, we return the predicted action (and possibly the associated mask) to the Arena Environment. Depending on the status of the executed action, we (7) return a dialogue response back to the user and update the interaction history stored in the controller. If the action is not executed successfully, we will process the error code returned from the environment and handle it accordingly.

3 Instruction Processing and Understanding

3.1 ASR Correction

Owing to the inherent instability of ASR systems, they may generate words that, while phonetically similar, are entirely distinct. This may result in sentences containing erroneous words that fail to accurately convey the user's intention, rendering them incomprehensible to our model. To address this issue, we developed and employed a post-processing methods for ASR output. Specifically, we systematically analyzed log files to identify and document recurrent and fixed-content ASR errors. These findings were recorded in a mapping file, which cataloged all high-frequency, fixed-context ASR errors. Should a user's voice input be recognized as one of these error contents, it would be directly translated into the appropriate command. For example, "let's chat" would be converted to "next challenge." It is important to note that, during the compilation of the mapping file, only error contents entirely unrelated to the task at hand were included. Should the error constitute a coherent and plausible command, it would be excluded from the mapping file to prevent misinterpretation of user instructions.

3.2 Co-reference Resolution

Motivation The goal of the co-reference resolution is to identify all the linguistic expressions such as pronounces that refer to the same real-world entity[1]. After grouping the expressions, one can replace the expressions with the name of the entity. Co-reference resolution is important in many high-level downstream tasks including natural language understanding, summarization, and question answering. Co-reference resolution is an important task in dialogue systems because it can maintain the coherence of machine-generated responses and allow the system to understand the users' utterances. Without co-reference resolution, the dialogue system may be confused with the users' intention and hence leads to a breakdown in the conversation.

Formulation Following [19], we formulate the task of co-reference resolution as a set of assignments for every span in the input text. If the total number of tokens in the input text is M, then there are $N = \frac{M(M+1)}{2}$ possible spans. The task of co-reference resolution is to assign each span i to an antecedent span j where $0 \leq j \leq i-1$. Hence the set of possible assignments for span i is $\{0, 1, ..., i-1\}$ where 0 denotes the dummy antecedent. If the dummy antecedent is selected, the current span is either not an entity or can not be connected with any previous span.

Approach We use the higher-order coreference resolution model proposed in [20], due to it strong performance. The model leverages bidirectional LSTMs to compute the text representations. Each time, the scoring module takes in the representations of the span i and one of its antecedent span j and compute the score indicating the possibility of assigning i to the antecedent span j. During inference, the higher-order coreference resolution model iteratively refines the span representations conditioned on higher-order structures and performs a coarse-to-fine antecedent pruning to reduce the computation cost of inference.[2]

3.3 Profanity Checking

Motivation With the expanding user base of online platforms, the presence of inappropriate content can rapidly accumulate, leading to a significant issue, especially in the context of online dialogue systems. Online dialogue systems generate responses based on users' input, and the presence of inappropriate language in the input can lead to the generation of inappropriate responses by the dialogue systems. This problem can have severe consequences such as damaging the brand's reputation, legal liability, and hurting the user experience. To address this issue, previously many efforts have been devoted to automatically detecting profanity language in dialogue systems. However, the traditional word-filter-based methods are not effective enough as inappropriate language depends on multi-dimensional factors such as the discourse context, the domain of the conversation, and the temporal relation between the conversation and world events. In our KnowledgeBot, we utilize a neural network-based profanity detection model, namely Profanity-Check, which offers low latency and high accuracy for detecting profanity in online dialogue systems.

Problem Formulation We formulate profanity checking into a text classification problem. Formally, given an utterance from a user, $\mathbf{w} \in \mathbf{X}$ and a binary set of classes $\mathcal{C} = \{0, 1\}$ where 0 denotes *not profanity* and 1 denotes *profanity*. The goal of this task is to train a classifier that maps the user utterances to classes: $f_\theta : \mathbf{X} \rightarrow \mathcal{C}$, where the function f is parameterized by θ.

Approach We select Profanity-Check[3] as our profanity checking model due to its low latency and high performance. Profanity-Check leverages the CountVectorizer class in scikit-learn to vectorize the input strings. The vectorizer computes the representations via Bag of Words. Profanity-Check uses Linear Support Vector Machine implemented by scikit-learn's LinearSVC class as the classifier f_θ. Table 1 shows the speed comparison between Profanity-Check and Profanity-Filter[4]. As one can observe, Profanity-Check is much more efficient.

[1] `https://web.stanford.edu/class/archive/cs/cs224n/cs224n.1162/handouts/cs224n-lecture10-coreference.pdf`

[2] We refer the reader to the original paper [20] for more details.

[3] `https://victorzhou.com/blog/better-profanity-detection-with-scikit-learn/`

[4] `https://pypi.org/project/profanity-filter/`

Model	1 Prediction (ms)	10 Prediction (ms)	100 Prediction (ms)
Profanity-Check	0.2	0.5	3.5
Profanity-Filter	60	1,200	13,000

Table 1: The time cost to make 1, 10, and 100 predictions by using Profanity-Check and Profanity-Filter.

Training Details The model is trained on a combined dataset collected from two publicly-available sources. (1) *Twitter* dataset is derived from a collection of tweets[5] scraped from Twitter. (2) *Wikipedia* dataset is from the Toxic Comment Classification Challenge [6] which consists of comments from Wikipedia's talk pages. Table 2 shows the statistics of the dataset:

Tweets	Not Offensive	Offensive	Total
Tweets	4,163 (16.8%)	20.620 (83.2%)	24,783(100%)
Wikipedia	143,346 (89.8%)	16,225 (10.2%)	159,571(100%)
Combined	147,509 (80.0%)	36,845 (20.0%)	184,354(100%)

Table 2: The statistics of the two datasets used to train Profanity-Check.

During training, the Profanity-Check leverages *squared hinge loss* which is the square of the standard hinge loss, set the tolerance for stopping criteria to 1e-2, and the maximum number of iterations to 1e5. All other hyperparameters are set to default as in the LinearSVC class.

3.4 Instruction Parsing

Our approach involves the utilization of an Instruction Parser module that is specifically designed to parse natural language instructions into machine-readable actions. In the design of this module, we have taken into account two crucial factors. Firstly, users may provide nested or compound instructions, which could involve multiple actions being mentioned in a single statement. Secondly, it is possible for users to mention important objects that are not the primary action target. For instance, a user may instruct the model to fetch an object in the kitchen, while the bot is situated in the lab. In this case, correctly detecting the name of the room is a prerequisite for completing the task.

Formally, given a natural language sentence, $\mathbf{w} = \{w_0.w_1, ..., w_n\}$, our Instruction Parser outputs a list of actions, consisting of an action predicate, a target object, and a list of other objects, $\mathbf{a} = \{a_0, a_1, ..., a_k | a_i = (p_i, o_i, e_i)\}$. To do so, we first utilize spaCy parser[7] to attach a part-of-speech (POS) tag and syntactic dependency relation for each token. Then we traverse the dependency tree to find a list of action predicates $[p_0, ..., p_k]$, for tokens whose POS tags are VERB. For each action predicate p_i subtree, we take its first noun child phrase as the action object o_i and all other nouns phrase as extra objects e_i. For example, given the instruction, `Place the control panel into the laser machine`, our Instruction Parser will yield an action tuple `(Place, control panel, [the laser machine])`.

4 Task Planning and Action Prediction

Performing task planning and action prediction given the user's instruction and the current environment is the core component of the framework. The first crucial challenge is how to accurately and robustly map the user instruction to an executable action plan for the assistive robot to complete everyday tasks. On the one hand, the actions and objects defined in an environment are often a fixed set since they need to be executable by robots. On the other hand, depending on different user profiles (e.g., geopolitics, age, etc.), the same action or object can have various expressions in verbal language to describe.

[5] `https://github.com/t-davidson/hate-speech-and-offensive-language/tree/master/data`

[6] `https://www.kaggle.com/c/jigsaw-toxic-comment-classification-challenge`

[7] `https://spacy.io/usage/linguistic-features`

Program	Input Instruction Example	Program Arguments	Output Action Sequence
BasicObjNavigation(obj)	pick up an apple	obj = Apple	(Goto, Apple), (PickUp, Apple)
EnhancedObjNavigation(obj)	pick up an apple	obj = Apple	(LookAround), (Goto, Apple), (PickUp, Apple)
GetPreqObj(main_obj, preq_obj)	place the milk on table	main_obj = Table, preq_obj = Milk	(Goto, Milk), (PickUp Milk), (Goto, Table), (Place, Table)
OpenContainer(main_obj, container)	pick up the milk in the fridge	main_obj = Milk, container = Fridge	(Goto, Fridge), (Open, Fridge), (Goto, Milk), (PickUp, Milk), (Close, Fridge)
UseTool(main_obj, tool)	heat the bread with microwave	main_obj = Bread, tool = Microwave	(Goto, Microwave), (Open, Microwave), GetPreqObj(Bread, Microwave), (Close, Microwave), (TurnOn, Microwave), (Open, Microwave), (PickUp, Bread), (Close, Microwave)

Table 3: **Symbolic reasoning programs**.

The second challenge is how to handle complex and composite instructions. Usually, the user will not directly use low-level instructions (e.g., `move forward, turn left`) that can be easily processed by the agent. Instead, they tend to use commands that are at a higher level and are more straightforward to humans. These instructions need to be decomposed into several actions such that the robot can successfully complete the task. For example, given a user's instruction `pick up the cake in the breakroom fridge`, the agent needs to break it down into an action sequence: `[(Goto, Breakroom), (Goto, Fridge), (Open, Fridge), (PickUp, Cake), (Close, Fridge)]`. As such, the robot needs to be capable of understanding and processing complex commands such that it can bridge the gap between human's instructions and executable robot action sequences.

In the following, we present our two different solutions to tackle the challenges above, respectively. We first describe an intuitive, robust, and extendable approach based on symbolic reasoning programs (Section 4.1), and then introduce a more generalizable neural PLANNER based on pre-trained language model associated with a neural action predictor, i.e., EXECUTOR (Section 4.2).

4.1 Instruction Following via Symbolic Reasoning

4.1.1 Action and Object Mapping

Given the parsed action tuples, our next step is to map the general action and objects expressions (e.g., `search a bowl`) into the finite action and object sets that are defined and executable in the Arena Environment (e.g., `(Find, Bowl)`). To achieve this, we apply mapping functions to map the actions and objects respectively. Specifically, we first predefine a comprehensive dictionary where the key is the executable action/object for the environment, and the value is a list of phrases that map to the action/object correspondingly. For a given action or object phrase from the parsed tuple, we traverse all the phrases in each list. When we find a matched action/object, we stop the program and return the matched action/object. If we cannot find a matched action/object after we traverse all the lists, we will return an empty action or object.

4.1.2 Decomposing Complex Instructions via Symbolic Reasoning Programs

While the instruction parser and the action/object mapping functions can already be used to predict the action sequence, they usually fail to handle complex or composite commands that cannot be parsed and mapped to executable commands. Also, in some cases, although the actions can be correctly processed, assistive actions (e.g., navigation) are still required to accurately execute the action as per requested by the user. As such, in order to build a robust agent that can handle various complex instructions and ensure a smooth user experience, we develop several symbolic reasoning programs that can be generally applicable to different scenarios. We list the most commonly used and important programs in practice in Table 3. Given the input instruction and the parsed tuples, the symbolic reasoning programs aim to augment the original *raw action tuples* to a more complete and executable action sequence.

Specifically, we elaborate on the following programs: (1) `BasicObjNavigation`: this is the most basic symbolic program that is executed every time the agent needs to interact with an object specified by the `Obj` argument. It is worth noting that the `goto` action is a navigation action supported

in the Arena Environment that can simplify the navigation process. The program can effectively mitigate the error type `TargetOutOfRange` since it can navigate the agent to a position that is close enough to interact with the object. (2) `EnhancedObjNavigation`: this is an enhanced version of `BasicObjNavigation`. It aims to handle the scenario when the grounding of `goto` action is failed because the required object does not occur in the agent's egocentric view. This program will prepend an additional `LookAround` action based on the two actions in `BasicObjNavigation`. As such, it can help the agent search for the object in its surrounding environment. If the agent still cannot find the object, then we roll back to a more complicated room-level navigation program that searches the entire room (described in Section 5.3). (3) `GetPreqObj`: in some scenarios, the action may involve two objects, such as `place the soda on the table` or `pour the milk into the bowl`. For such actions, we define a program that takes in two arguments: `main_obj`, i.e., the target/destination object of the action (e.g., table or bowl), and `preq_obj` standing for the prerequisite object that needs to be held in robot's hand in the first place. This program ensures the robot must have been holding the prerequisite object before it executes the action. Note that this program is only executed when the `preq_obj` is not currently at the robot's hand. (4) `OpenContainer`: some actions involve a main object (`main_obj`) and a `container` that holding the main object. The `OpenContainer` program is thus designed to first navigate to the container, open the container, and then pick up the main object. (5) `UseTool`: some actions require to use an instrument or tool such as a microwave or time machine to complete the instruction, which needs a more complicated sequence of actions. Therefore, we design the `UseTool` program that predicts a long sequence of actions.

To sum up, these general symbolic reasoning programs enable our KnowledgeBot to robustly execute complex instructions that require commonsense reasoning.

4.2 Task Planning via Pre-trained Language Models

Inspired by how humans complete tasks, this method emulates this process. A person typically begins with a high-level plan and then adapts and improves the plan based on the surroundings. Therefore, we propose a new hierarchical structure of task completion that first creates high-level sub-goal instructions, then generates primitive actions by combining the generated high-level instructions with environmental context. Our model consists of a PLANNER that produces high-level sub-goal instructions from high-level tasks (e.g., "Make Coffee") and an EXECUTOR that generates primitive actions conditioned on generated sub-goal instructions and environment context.

4.2.1 Planner

We investigated two variants of Planner, as illustrated in Figure 3. We adopt T5 [35] as the backbone of Planner's encoder and decoder structure.

Complete Generation For this variant, we employed T5-large to train an additional object generator that generates relevant object information for the task. First, the object generator takes in task description $\mathbf{g}$ and outputs a list of involved objects $\hat{\mathbf{o}}$. Then, we take the generated objects $\hat{\mathbf{o}}$ as discrete prompts and concatenate them with the task description $\mathbf{g}$ to form the input for the encoder.

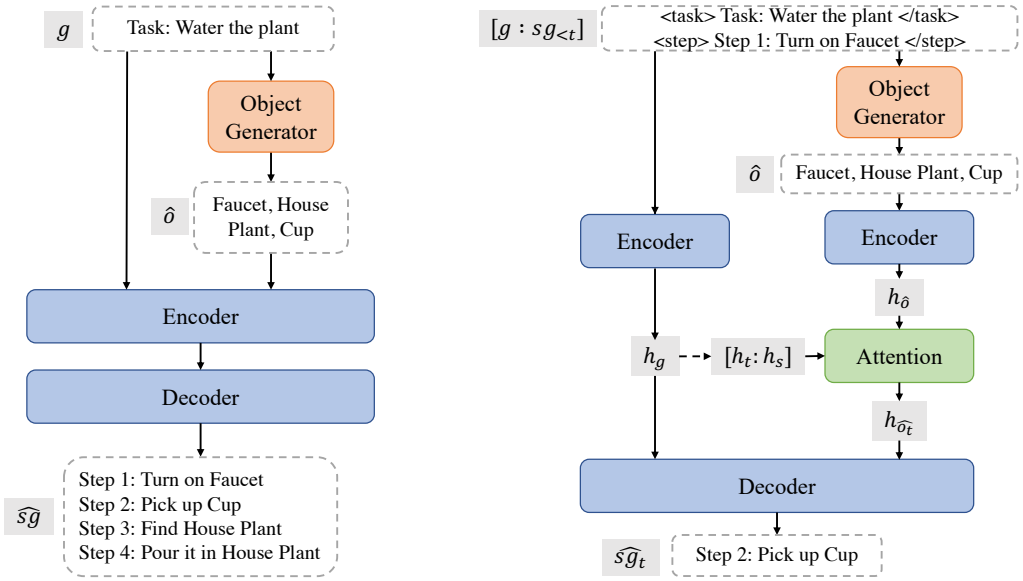
Step-by-step Generation The input for this variant is the concatenation of task description $\mathbf{g}$ and history sub-goal sequence $\mathbf{sg_{<t}}$. We also introduced two special token pairs `<task>, </task>` and `<steps>, </steps>` to mark the beginning and end of the task and steps, respectively.

We use the same object generator as in Complete Generation to incorporate object information. However, instead of directly utilizing the entire generated object list $\hat{\mathbf{o}}$, we applied the attention mechanism to compute the representation of the current object $\mathbf{o_t}$. Specifically, we concatenate the last hidden state of `<task>` and `<steps>` from the encoder and use the concatenated hidden states $[h_t : h_s]$ as the query. We obtain the current object states $h_{\hat{o}_t}$ as follows:

$$h_{\hat{o}_t} = \text{Attention}(Q = [h_t : h_s], K = h_{\hat{o}}, V = h_{\hat{o}}) \tag{1}$$

$$= \text{Softmax}(\frac{QK^T}{T})V \tag{2}$$

where $h_{\hat{o}}$ denotes the representations of the object lists and T denotes the temperature term. We set a small value of T to enforce the approximated hard attention on one single object.



(a) Complete Generation (b) Step-by-step Generation

Figure 3: **Overview of two variants of the Planner.** (a) **Complete Generation** takes the task description $\mathbf{g}$ as input and generates the complete sub-goal sequence. (b) **Step-by-step Generation** takes the concatenation of the task description $\mathbf{g}$ and history sub-goal sequence $\hat{\mathbf{sg}}_{<\mathbf{t}}$ as input and generate the current sub-goal $\hat{\mathbf{sg}}_{\mathbf{t}}$.

Subsequently, we use the current object states $h_{\hat{o}_t}$ as a soft prompt and concatenate it with the context encoding h_g from the encoder, and feed the concatenated hidden states as input to the decoder. The decoder then generate the current sub-goal $\hat{\mathbf{sg}}_{\mathbf{t}}$.

Implementation Details We train both the PLANNER and object generator using T5-large with a batch size of 6 and a learning rate of 3e-05.

5 Visual Understanding and Navigation

5.1 Object Detection

Given the object class $O_{instruction}$ predicted based on the user instruction, the target of the object detection module is to extract the corresponding one or multiple image masks from the images collected in the Arena environment for the current view. We first apply a Mask-RCNN image segmentation model [13] trained on the vision dataset 8.1.1 to extract object masks and their corresponding visual object classes $\{V^1_{image}, V^2_{image}, ..., V^n_{image}\}$ from the observed images. We then map the object class $O_{instruction}$ in the instruction to the corresponding visual object class $V_{instruction}$ based on the predefined dictionary. We finally obtain all image masks $\{M_i, M_j, ...\}$ with the visual object class $V^i_{image} = V^j_{image} = V_{instruction}$.

5.2 Visual Grounding

In the case that we obtain multiple image masks from the object detection module, the visual grounding module is designed to choose the best-matched mask with respect to the instruction. Two grounding strategies are applied, namely *Area Grounding*, where we choose the mask with the biggest area, and *Color Grounding*, where we choose the mask whose corresponding object has the dominant color most similar to the expected color mentioned in the instruction if any.

Algorithm 1: Viewpoint-based Navigation with Visual Grounding

Input: Query object class q associated with its attribute set $\mathcal{A}$, the viewpoint list in the current room $\mathcal{V} = [v_1, ..., v_n]$, segmentation model f, grounding model g.

Output: Predicted mask for the query object M_{out}.

Initialize the best attribute distance d_{min} as $+inf$;
Initialize the predicted object mask M_{out} as $\emptyset$;
for v_i *in* $\mathcal{V}$ **do**
    Execute (`Goto`, v_i);
    Execute (`LookAround`) and obtain an egocentric image list $\mathcal{I} = [h_1, ..., h_e]$ at v_i;
    for h_j *in* $\mathcal{I}$ **do**
        $\{(c_k, M_k)\} \leftarrow f(h_j)$; /* Predict the object class c_k and associated segmentation mask M_k for the image h_j. */
        for *each* (c_k, M_k) **do**
            if $c_k == q$ **then**
                $d_k \leftarrow g(M_k, h_j, \mathcal{A})$; // Compute the attribute distance for M_k.
                if $d_k < d_{min}$ **then**
                    $d_{min} = d_k$; // Update the minimal attribute distance.
                    $M_{out} = M_k$; // Update the output mask.
        end
    end
    if $M_{out} != \emptyset$ **then**
        return M_{out} ; // Found an matched object and return the mask.
end
return M_{out} ; // Cannot find the object in the current room.

To extract the dominant color for the detected object, we design the color detector based on [8]. We first apply the mask to the original image to crop out the detected object. We then use k-mean with the cluster_number=3 to cluster RGBA color values of its pixels to get the dominant color value. Note that the obtained dominant color value, like 00FF01, may not exactly match the color value, like 00FF00(green), from the instruction. So we further apply a distance-based method to map the dominant color to one of the pre-defined color candidates, like {red, blue, green, white, yellow}, which exists in the Arena environment. In detail, we convert the dominant color value to the cie space[9] so that we can compute the Delta E (CIE2000) distance [38] between the clustered dominant color value and the candidate colors and obtain the predicted dominant color within the candidates and its Delta E (CIE2000) distance. The mask with the minimum distance will be chosen as the predicted mask for the object mentioned in the instruction.

5.3 Navigation

In Section 4.1.2 we have introduced two symbolic reasoning programs that are for basic navigation, i.e., `BasicObjNavigation` and `EnhancedObjNavigation`. In this section, we further elaborate on how we design the viewpoint-based navigation program.

Particularly, when the required object still cannot be found after executing `BasicObjNavigation` and `EnhancedObjNavigation` programs, we then start our viewpoint-based navigation as presented in Algorithm 1. If the navigation program still cannot find the query object after searching for the entire room, then the robot will return an error-handling dialogue to the user and instruct them to try to search other rooms or read the hint. Note that the viewpoint list and the `goto viewpoint` action are pre-defined in the Arena Environment.

6 Situated Dialogue Response

To effectively tackle complex real-world tasks, a nuanced approach is required to address the diverse range of situations that may arise. Our proposed solution is a Situated Dialogue Response module that

[8] `https://pypi.org/project/dominant-color-detection/`
[9] `https://en.wikipedia.org/wiki/CIE_1931_color_space`

Case	User Instruction Example	Robot Response
Greeting	"Let's get started."	"Great! Let us get the job done together!"
Action Successful	"move forward"	"Done. What's next?"
Ask for Task Guidance	"What can I do in this game?"	"The task is displayed on the top-left corner of your screen and the map is displayed on the top-right corner. Simply tell me the first step to start. You can also say read the sticky note to know more about the task."
Ask for Clarification	"take"	"Sorry, I only heard 'take'. Could you try it again or give me more details?"
Long Action Sequence	"pick up the milk from fridge and pour it into the bowl."	"Got it. I will do it for you."
Start Navigation	"find a trophy in this room"	"Searching 'trophy' for you."
Encounter Block	N/A	"Is there a box blocks the way? If yes, please say turn on robotic arm and I will remove it for you. If no, please continue."
Object Not Found	"find a trophy in this room"	"Sorry, I cannot find 'trophy' in this room. Could you try it again or try another room?"
No Action Predicted	"increase the brightness of the device"	"Sorry, I do not know how to do this. Could you try again or give me more details on how to complete the task step by step? You can also try to find and read a sticky note for hints."
Failed Coreference	"place it on table."	"Sorry, I do not know which one you are referring to. Can you say it again with more details?"
Profanity Checking	"pick up a knife and kill yourself."	"Sorry, I cannot help you with that."

Table 4: Examples of situated dialogue response. ***Note: all the user instruction and robot response examples presented in this table come from the team's interaction and they are not from real customer interaction.***

utilizes template-based methods to generate responses tailored to each unique case. This approach enables us to provide sophisticated and context-specific to accommodate a diverse range of scenarios. Examples of situated dialogue responses are shown in Table 4

To initiate a conversation, Greeting templates are utilized to welcome the user. In order to cater to different requested instruction statuses, we propose four distinct types of templates. These templates include the Action Successful template which serves as a closure for the current task while also enabling the bot to commence a new task if required. The Ask for Task Guidance template is used in instances where the user requests guidance to complete the task, while the Ask for Clarification template is utilized when the bot requires additional information to execute the task. We also provide a response template for instances where the bot is given a Long Action Sequence. In navigation-related scenarios, we offer three distinct response templates. These include the Start Navigation template to initiate navigation, the Encounter Block template if an object blocks the bot's intended action, and the Object Not Found template if the requested object cannot be located. In addition, we have designed a template to address situations where the bot fails to find the coreference for an ambiguous pronoun. Lastly, we provide a response template if the instruction fails Profanity Checking.

7 Controller and Error Handler

In addition to the components for processing and predicting the action sequence, as well as the visual grounding and navigation modules, we also need a *higher-level controller and error handler* to combine the separate modules into a whole working system and handle the exceptions that may occur in different components. In the following, we will introduce how we store important interaction information via an Internal Memory, and then elaborate on how we design the Controller that controls the action flow and update the Internal Memory. Finally, we will describe how we handle the exceptions that occurred during executing the actions in the environment.

7.1 Internal Memory for User Interaction

During the interaction with the user, it is essential to keep track of the important information such that the agent can execute the actions that require knowing the current state. For example, to execute

Internal Storage Variable	Description
Instruction History	Store the user instructions history during interaction.
Object in Hand	Keep track of the object that is held by the robot.
Number of Interaction Rounds	Record how many rounds of interaction have proceeded.
Navigation Object	Record the query object during navigation.
Previous Session ID	Record the session ID to determine if a new game is launched.
Consecutive Error	A boolean value to record if the robot encounters errors in two consecutive interactions.

Table 5: Internal storage variables and associated descriptions.

the actions for `place the milk on table`, the agent needs to first confirm if *milk* is on its hand. If not, then the agent needs to first execute the `GetPreqObj` program to fetch the milk.

We present the essential storage variables in Table 5. Specifically, (1) the `Instruction History` is used to store users' instruction history so that we can refer back to previous instructions when we need them; (2) we use `Object in Hand` to record the object that is holding on the robot's hand so that we can determine if the robot needs to go and fetch an object; (3) the `Previous Session ID` aims to check if the session ID of interactions is changed. If so, then we will clear some internal storage such as `Instruction History`, `Object in Hand`, and `Number of Interaction Rounds`; (4) we use `Consecutive Error` to record whether the robot consecutively encounters errors during interactions. If so, we will give a more detailed instructions on how to play the game and find the hint to complete the tasks.

7.2 Controller

The task planner or action prediction module can predict multiple actions at a time (i.e., action plan). However, many action sequences cannot be directly returned to Arena Environment at a time and each of the actions in the sequence needs to be returned sequentially. Meanwhile, when some actions are executed successfully, we need to update the Internal Storage correspondingly. As such, we design a Controller to control the action execution flow.

7.3 Error Handler

In order to optimize human-machine interaction processes specifically for various error types, we designed a refined error handler. After analyzing numerous actual cases, we matched each error type with corresponding practical arena scenarios. We identified 14 distinct error types and devised corresponding dialogue responses based on the error codes returned from the Arena Environment. When users' utterances are inappropriate or erroneous, the error handler can provide targeted responses and guide users to offer correct, recognizable instructions.

For instance, when the action specified in the user utterance cannot be executed in the Simbot arena, the error handler identifies this category of error and returns: "This action is not supported. Could you please try something else?", prompting the user to change the action instruction. Table 6 displays the 14 error types and their respective response statements.

If none of the predefined error types match the generated error, the error handler will return a default error response. Throughout the optimization process, we continually monitor default error cases (indicating error types unaddressed by the current handler) and update the error handler accordingly to encompass all potential error types.

Error Code	Error Handler's Response
Default	"Sorry, something went wrong. Please try it again and maybe say it in a different way."
UnsupportedAction	"This action is not supported. Could you please try something else?"
UnsupportedNavigation	"I cannot move this way. Could you try something else, such as turn around?"
AlreadyHoldingObject	"I'm already holding an object. Could you please first put the object somewhere?"
ReceptacleIsFull	"The receptacle is full. Please first try to empty it."
ReceptacleIsClosed	"The receptacle is closed. Please first try to open it."
TargetInaccessible	"I cannot access the object you specify. Please try to guide me there or try something else."
TargetOutOfRange	"The target is out of range. Can you direct me to be closer to it?"
InterruptedByNewCommandBatch	"I am interrupted by a new command. Please instruct me step by step."
ObjectUnpowered	"The object is not powered. Please first turn on the power."
ObjectOverloaded	"The object is overloaded. Please first try to fix it or try something else."
NoFreeHand	"I don't have free hands. Please first place the object in my hand to somewhere. "
InvalidCommand	"The command is invalid. Please try other instructions."
ObjectNotPickedUp	"I am not holding the object. Please first try to pick it up."

Table 6: Dialogue responses for error handler.

8 Experiments

8.1 Experiment Setups

8.1.1 Dataset

Alexa Arena The Alexa Arena [10] is a simulation platform for user-centric Embodied AI and it is the core platform for the Simbot Challenge and our KnowledgeBot system. We use the vision dataset to train our vision model, and use the instruction following benchmark to evaluate our task planner and action predictor. Specifically, we use the validation set of the dialog-guided task completion benchmark for evaluation. It contains 383 tasks with 1149 sessions. On the other hand, the vision dataset in the Arena Environment contains 600k training images spanning 336 unique objects, which are collected from the Arena environment. These visual data are generated by initializing game missions and then navigating to all the different objects present in the scene and capturing the corresponding egocentric view image.

TEACh We use the Execution from Dialogue History (EDH) subtask in the TEACh [33] dataset to train and evaluate the neural planner model. Each EDH instance consists of four components, (S^E, A_H, A_R^I, F^E), where S^E is the initial state of the EDH instance, A_H is an action history, and the agent is tasked with predicting a sequence of actions that changes the environment state to F^E, using A_R^I reference interaction actions taken in the session as supervision. To train the neural planner model, we leverage the action history A_H and reference interaction actions A_R^I as input and target output. TEACh dataset contains 5475 EDH Instances, 608 and 666 seen instances for validation and test, and 2157 and 2270 unseen instances for validation and test.

Models	Unseen SR	Seen SR
Alexa Prize Team Baseline	9.70	12.46
PLANNER (COMPLETE)	**11.42**	**12.31**

Table 7: Unseen Success Rate (SR) (%) and Seen SR (%) on TEACh unseen test set.

Models	Unseen SR
PLANNER (STEP-BY-STEP)	12.9
PLANNER (COMPLETE)	**13.6**

Table 8: Unseen Success Rate (SR) (%) on TEACh unseen validation set.

8.1.2 Evaluation

For the instruction following benchmark on Arena, we use the *Goal Completion* that calculates the fraction of the game sessions our agent can successfully accomplish. For the evaluation on TEACh, we use *Unseen Success Rate* which computes the fraction of tasks that all expected state changes are present after the agent finished all the actions.

In addition to evaluating our model on instruction following benchmarks, we also actively analyze the user ratings and feedback throughout the whole user interaction phases. Due to privacy policy, we do not show detailed examples of user feedback and interaction history in this report.

8.2 Results for Instruction Following

Arena The Goal Completion rate of our approach on the Alexa Arena environment is **0.96%**, where we use symbolic reasoning to perform the instruction following. We found that our model performs worse in the offline evaluation compared to the online evaluation. We hypothesize this is caused by the following reasons: (1) the logic flow we design is mainly for the online scenario and it did not fit the offline code base well; (2) our designed symbolic programs may not be general enough; (3) real human users can try the instructions on different levels, where the low-level instructions can be more easily understood by our model. Due to the time constraint we did not extensively apply A/B test to evaluate the effectiveness of our symbolic programs.

TEACh We first present the instruction following performance on the Execution from Dialogue History (EDH) subtask in TEACh to demonstrate the effectiveness of our neural PLANNER model proposed in Section 4.2. As shown in Table 7, our PLANNER model achieves a very promising improvement over the baseline by 1.72%. We also show the comparison between the step-by-step and complete planner in Table 8. We found that the planner with complete steps is better than the one with step-by-step.

8.3 Error Analysis and Remaining Challenges

High-level Command There are still a few high-level commands that could not be handled by our instruction processing and understanding modules. These high-level commands are split into 3 cases: (1) the command only contains some high-level action and goal, without detailed executable operation and information. For example, from the command "Change the white bowl to red", our module cannot generate the complete action list "go to the quantum lab. find the color changer. put the bowl on the color changer. turn on the color changer." because it lacks the information about *quantum* and *color changer*. (2) the command includes some complex concepts, for example, the relative position concept. For the command "go in front of the table", our model can only plan the "go to the table" action but could not figure out the relative position between Simbot and the table. (3) The utterance is more of a conversation than a direct order. For utterances like "This is the door I'm looking for," our model can't use the user's previous command history to infer that what they really want to say is "find another door."

Error Type	Error Example Utterance	Note
High-level command	Change the white bowl to red	The model can only understand operation, but cannot infer the procedure of a high-level task.
	This is the door i'm looking for	The model cannot understand utterances requiring a previous command history.
	Go in front of the table	The model cannot understand the relative position concept.
ASR error	Let's chat	The actual command is "Next Challenge". The ASR returns similar pronunciation but incorrect words.
	Play the app on the color change	The actual command is "Place". The ASR returns similar pronunciation but incorrect words.
	Cancel we build a support from sideways fifty times	The command is not a fluent English sentence.
Target ambiguous	Go in the room	No specific room name is given, and there is no door or room in the viewpoint.
	Go to the lab	Not clarify which lab the user would like to go.
Out of capability	What is the weather in hallettsville texas tomorrow?	The simbot cannot answer the real-world question.
	Alexa walk sideways	The action is pre-defined.
	Put-down the box	There is no "box" object in the arena.
Task-irrelevant command	Alexa we're done	The utterance itself is not a command for an operation or action.
	Ghost rider	The utterance is entirely task-irrelevant.
Question utterance	Can you see the redshelf?	The model cannot answer user's question, and only can understant action command.

Table 9: Analysis of remaining errors.

ASR Error The incorrect ASR result may include similar pronunciation but entirely different words. This kind of error may lead to: (1) unreadable sentences, or (2) fluent but semantically wrong sentences. In the first case, the model is not able to deal with such utterances. For the second case, the model may execute actions that are not what the user wants to do.

Target Ambiguous Our model cannot figure out ambiguous targets based on the current situation and high-level task goals. If the user does not specify the target in the utterance, the model cannot generate corresponding actions.

Out of Capability Some commands are out of the capability of the Simbot. The Simbot cannot answer questions like "What is the weather in Hallettsville texas tomorrow?", or execute undefined actions like "walk sideways".

Task-irrelevant Command Some utterances are task-irrelevant. For example, "Ghost rider".

Question Utterance When the user tries to ask a question to determine the situation, our model cannot give the correct response. For the utterance "Can you see the red shelf?", the user would like to check if the Simbot recognizes the red shelf first, and then do the following actions. However, our current model can only handle pre-defined questions.

9 Related Works and Future Directions

9.1 Multimodal Pretraining

Recent studies in multimodal pretraining have shown promising results in enabling multimodal models to perform various tasks and induce zero-shot capability. For instance, VL-T5 [5] addresses vision-and-language tasks by formulating them into a unified text generation task. Similarly, Flamingo [2]

is trained on large-scale arbitrary interleaved multimedia corpora, allowing it to perform in-context few-shot learning. BEiT-3 [43] treats images as foreign languages and performs masked language objectives on images, texts, and image-text pairs. OFA [42] further extends text-only generation tasks to image generation. Uni-Perceiver v2 [21] is jointly trained on various multimodal tasks and can perform downstream tasks without task-specific adaptation. Additionally, MultiInstruct [45] proposes a large-scale multimodal instruction tuning dataset that further improves the generalizability of pre-trained multimodal models via instruction tuning. Finally, BLIP-2 [22] bridges a frozen pre-trained language model with a frozen pre-trained image encoder by a two-stage bootstrapping process. These advancements in multimodal pretraining demonstrate the potential of these models to tackle complex tasks and offer new opportunities for the development of general AI systems.

9.2 Embodied Vision-Language Planning

Recent advances in embodied AI and multimodal machine learning have given rise to various tasks in embodied vision-language planning tasks, such as Vision-Language Navigation (VLN) [3, 9, 16, 11], Vision-and-dialog Navigation [6, 32, 40], and Vision-Dialog Navigation and Task Completion [31, 39, 33, 48, 10]. This line of research aims to combine natural language commands with visual perception and physical action, empowering agents to navigate through embodied environments and perform diverse tasks. There are two main directions in this field. The first direction focused on building a unified multimodal model that can encode historical information from language, images, and action to predict the next action [34, 7]. One notable example is PaLM-E[7], a large embodied multimodal language model that can perform a variety of embodied reasoning tasks. The other direction utilizes the strong reasoning capabilities of large pre-trained language model (PLLM) for task planning and then grounds the plan to the environment [48, 17]. For instance, SayCan [1] proposes to ground language models in agents' affordances by combining the candidate action's probability from PLLM with the action's affordance value. Furthermore, Inner Monologue [17] proposes to incorporate environment feedback into the LLM through natural language and combines large language model planning with robotic control policies.

9.3 Dialogue System For Task-oriented Embodied Agent

Task-oriented dialogue is a key area of research that aims to enable effective communication between humans and machines. To achieve this goal, most works in this field focus on several key components: (1) an intent detection to understand the user's goals and needs [23]; (2) a dialogue state tracking module that helps to keep track of the constraints imposed by the user, which can be useful for guiding the conversation towards a successful outcome [29, 39, 15, 41, 30]; (3) a dialogue policy used to determine system actions that can help to achieve the user's objectives [47]. By paying attention to these key components, researchers in the field of task-oriented dialogue are helping to create more effective and efficient dialogue systems that can better serve human needs. In addition to task-oriented dialogue systems under the supervised setting, many prior works also explore applying continual learning techniques [18, 27, 25] such that the dialogue system can continually evolve in a dynamic environment [28], which is especially important for the agents in the embodied environment.

9.4 Visual Understanding in Embodied Environment

Significant advancements in the visual understanding field have been made through research in various subfields, such as semantic/instance segmentation [26, 14, 46, 24] and object detection [37, 36]. FCN [26] introduced a fully convolutional architecture for semantic segmentation, while Faster R-CNN [37] revolutionized object detection with the use of Region Proposal Networks. Mask R-CNN [14] extended the Faster R-CNN framework for instance segmentation by adding a mask prediction branch. ADE20K [49], a comprehensive dataset for scene parsing, has become a standard benchmark for evaluating semantic segmentation algorithms. In addition, the YOLO [36] approach streamlined real-time object detection by predicting bounding boxes and class probabilities directly from a single convolutional network. On the other hand, based on the previous work, research in the visual understanding field for embodied environments has produced notable results, with works such as [8], which presents a self-improving embodied object detection approach that combines reinforcement learning and supervised fine-tuning. Cognitive mapping and planning for visual navigation tasks in embodied settings are explored in [12], introducing a method that learns to build a top-down belief map and plans paths using a differentiable planner. In [44], the authors tackle Embodied

Question Answering (EQA) tasks in photorealistic environments using point cloud perception, developing a model that reasons about its surroundings to answer questions. Lastly, [4] focuses on learning exploration policies for navigation in embodied environments, using an unsupervised learning framework to train a neural network policy that effectively guides agents to explore novel regions. These works highlight the potential of combining visual understanding with embodied AI for creating intelligent agents, shaping the direction of future research in the field.

10 Conclusion

In this work, we present KnowledgeBot, a conversational embodied agent designed to complete real-life tasks by interacting with users for the Alexa SimBot Challenge. By combining natural language processing, computer vision, task planning, and execution, KnowledgeBot is able to handle an enormous variety of user-defined tasks, possess the ability to perform complex reasoning and visual comprehension to effectively carry out actions in the physical world, and engage in natural and seamless interactions with humans to ensure an optimal user experience. Overall, we believe the development of intelligent assistive agents like KnowledgeBot has the potential to revolutionize the way individuals interact with machines and complete their daily tasks.

References

[1] M. Ahn, A. Brohan, N. Brown, Y. Chebotar, O. Cortes, B. David, C. Finn, K. Gopalakrishnan, K. Hausman, A. Herzog, et al. Do as i can, not as i say: Grounding language in robotic affordances. *arXiv preprint arXiv:2204.01691*, 2022.

[2] J. Alayrac, J. Donahue, P. Luc, A. Miech, I. Barr, Y. Hasson, K. Lenc, A. Mensch, K. Millican, M. Reynolds, R. Ring, E. Rutherford, S. Cabi, T. Han, Z. Gong, S. Samangooei, M. Monteiro, J. Menick, S. Borgeaud, A. Brock, A. Nematzadeh, S. Sharifzadeh, M. Binkowski, R. Barreira, O. Vinyals, A. Zisserman, and K. Simonyan. Flamingo: a visual language model for few-shot learning. *CoRR*, abs/2204.14198, 2022.

[3] P. Anderson, Q. Wu, D. Teney, J. Bruce, M. Johnson, N. Sünderhauf, I. Reid, S. Gould, and A. Van Den Hengel. Vision-and-language navigation: Interpreting visually-grounded navigation instructions in real environments. In *CVPR*, 2018.

[4] T. Chen, S. Gupta, and A. Gupta. Learning exploration policies for navigation. *arXiv preprint arXiv:1903.01959*, 2019.

[5] J. Cho, J. Lei, H. Tan, and M. Bansal. Unifying vision-and-language tasks via text generation. *CoRR*, abs/2102.02779, 2021.

[6] H. De Vries, K. Shuster, D. Batra, D. Parikh, J. Weston, and D. Kiela. Talk the walk: Navigating new york city through grounded dialogue. *arXiv:1807.03367*, 2018.

[7] D. Driess, F. Xia, M. S. Sajjadi, C. Lynch, A. Chowdhery, B. Ichter, A. Wahid, J. Tompson, Q. Vuong, T. Yu, et al. Palm-e: An embodied multimodal language model. *arXiv preprint arXiv:2303.03378*, 2023.

[8] Z. Fang, A. Jain, G. Sarch, A. W. Harley, and K. Fragkiadaki. Move to see better: Self-improving embodied object detection. *arXiv preprint arXiv:2012.00057*, 2020.

[9] D. Fried, R. Hu, V. Cirik, A. Rohrbach, J. Andreas, L.-P. Morency, T. Berg-Kirkpatrick, K. Saenko, D. Klein, and T. Darrell. Speaker-follower models for vision-and-language navigation. *NeurIPS*, 2018.

[10] Q. Gao, G. Thattai, X. Gao, S. Shakiah, S. Pansare, V. Sharma, G. Sukhatme, H. Shi, B. Yang, D. Zheng, et al. Alexa arena: A user-centric interactive platform for embodied ai. *arXiv preprint arXiv:2303.01586*, 2023.

[11] J. Gu, E. Stefani, Q. Wu, J. Thomason, and X. E. Wang. Vision-and-language navigation: A survey of tasks, methods, and future directions. *arXiv preprint arXiv:2203.12667*, 2022.

[12] S. Gupta, J. Davidson, S. Levine, R. Sukthankar, and J. Malik. Cognitive mapping and planning for visual navigation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2616–2625, 2017.

[13] K. He, G. Gkioxari, P. Dollár, and R. Girshick. Mask r-cnn. In *Proceedings of the IEEE international conference on computer vision*, pages 2961–2969, 2017.

[14] K. He, G. Gkioxari, P. Dollár, and R. Girshick. Mask r-cnn. In *2017 IEEE International Conference on Computer Vision (ICCV)*, pages 2980–2988, 2017.

[15] M. Henderson, B. Thomson, and S. Young. Deep neural network approach for the dialog state tracking challenge. In *Proceedings of the SIGDIAL 2013 Conference*, pages 467–471, Metz, France, Aug. 2013. Association for Computational Linguistics.

[16] Y. Hong, Q. Wu, Y. Qi, C. Rodriguez-Opazo, and S. Gould. Vln bert: A recurrent vision-and-language bert for navigation. In *CVPR*, 2021.

[17] W. Huang, F. Xia, T. Xiao, H. Chan, J. Liang, P. Florence, A. Zeng, J. Tompson, I. Mordatch, Y. Chebotar, et al. Inner monologue: Embodied reasoning through planning with language models. *arXiv preprint arXiv:2207.05608*, 2022.

[18] J. Kirkpatrick, R. Pascanu, N. Rabinowitz, J. Veness, G. Desjardins, A. A. Rusu, K. Milan, J. Quan, T. Ramalho, A. Grabska-Barwinska, et al. Overcoming catastrophic forgetting in neural networks. *Proceedings of the national academy of sciences*, 114(13):3521–3526, 2017.

[19] K. Lee, L. He, M. Lewis, and L. Zettlemoyer. End-to-end neural coreference resolution. In M. Palmer, R. Hwa, and S. Riedel, editors, *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, EMNLP 2017, Copenhagen, Denmark, September 9-11, 2017*, pages 188–197. Association for Computational Linguistics, 2017.

[20] K. Lee, L. He, and L. Zettlemoyer. Higher-order coreference resolution with coarse-to-fine inference. In M. A. Walker, H. Ji, and A. Stent, editors, *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 2 (Short Papers)*, pages 687–692. Association for Computational Linguistics, 2018.

[21] H. Li, J. Zhu, X. Jiang, X. Zhu, H. Li, C. Yuan, X. Wang, Y. Qiao, X. Wang, W. Wang, and J. Dai. Uniperceiver v2: A generalist model for large-scale vision and vision-language tasks. *CoRR*, abs/2211.09808, 2022.

[22] J. Li, D. Li, S. Savarese, and S. C. H. Hoi. BLIP-2: bootstrapping language-image pre-training with frozen image encoders and large language models. *CoRR*, abs/2301.12597, 2023.

[23] B. Liu and I. Lane. Attention-based recurrent neural network models for joint intent detection and slot filling. pages 685–689, 09 2016.

[24] L. Liu, J. Cao, M. Liu, Y. Guo, Q. Chen, and M. Tan. Dynamic extension nets for few-shot semantic segmentation. In *Proceedings of the 28th ACM International Conference on Multimedia*, MM '20, page 1441–1449, New York, NY, USA, 2020. Association for Computing Machinery.

[25] M. Liu, S. Chang, and L. Huang. Incremental prompting: Episodic memory prompt for lifelong event detection. In *Proceedings of the 29th International Conference on Computational Linguistics*, pages 2157–2165, Gyeongju, Republic of Korea, Oct. 2022. International Committee on Computational Linguistics.

[26] J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. In *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3431–3440, 2015.

[27] D. Lopez-Paz and M. Ranzato. Gradient episodic memory for continual learning. In *Advances in Neural Information Processing Systems*, pages 6467–6476, 2017.

[28] A. Madotto, Z. Lin, Z. Zhou, S. Moon, P. Crook, B. Liu, Z. Yu, E. Cho, P. Fung, and Z. Wang. Continual learning in task-oriented dialogue systems. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 7452–7467, Online and Punta Cana, Dominican Republic, Nov. 2021. Association for Computational Linguistics.

[29] S. Y. Min, D. S. Chaplot, P. Ravikumar, Y. Bisk, and R. Salakhutdinov. Film: Following instructions in language with modular methods. *ArXiv*, abs/2110.07342, 2021.

[30] N. Mrkšić, D. Ó Séaghdha, T.-H. Wen, B. Thomson, and S. Young. Neural belief tracker: Data-driven dialogue state tracking. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1777–1788, Vancouver, Canada, July 2017. Association for Computational Linguistics.

[31] A. Narayan-Chen, P. Jayannavar, and J. Hockenmaier. Collaborative dialogue in minecraft. In *ACL*, 2019.

[32] K. Nguyen and H. Daumé III. Help, anna! visual navigation with natural multimodal assistance via retrospective curiosity-encouraging imitation learning. *arXiv:1909.01871*, 2019.

[33] A. Padmakumar, J. Thomason, A. Shrivastava, P. Lange, A. Narayan-Chen, S. Gella, R. Piramuthu, G. Tur, and D. Hakkani-Tur. Teach: Task-driven embodied agents that chat. *arXiv:2110.00534*, 2021.

[34] A. Pashevich, C. Schmid, and C. Sun. Episodic transformer for vision-and-language navigation. In *CVPR*, 2021.

[35] C. Raffel, N. Shazeer, A. Roberts, K. Lee, S. Narang, M. Matena, Y. Zhou, W. Li, and P. J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *The Journal of Machine Learning Research*, 21(1):5485–5551, 2020.

[36] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi. You only look once: Unified, real-time object detection. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 779–788, 2016.

[37] S. Ren, K. He, R. Girshick, and J. Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. In C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 28. Curran Associates, Inc., 2015.

[38] G. Sharma, W. Wu, and E. N. Dalal. The ciede2000 color-difference formula: Implementation notes, supplementary test data, and mathematical observations. *Color Research & Application: Endorsed by Inter-Society Color Council, The Colour Group (Great Britain), Canadian Society for Color, Color Science Association of Japan, Dutch Society for the Study of Color, The Swedish Colour Centre Foundation, Colour Society of Australia, Centre Français de la Couleur*, 30(1):21–30, 2005.

[39] M. Shridhar, J. Thomason, D. Gordon, Y. Bisk, W. Han, R. Mottaghi, L. Zettlemoyer, and D. Fox. Alfred: A benchmark for interpreting grounded instructions for everyday tasks. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 10740–10749, 2020.

[40] J. Thomason, M. Murray, M. Cakmak, and L. Zettlemoyer. Vision-and-dialog navigation. In *CoRL*, 2020.

[41] J. Wang, M. Liu, and X. Quan. Progressive dialogue state tracking for multi-domain dialogue systems. In *ICASSP 2021 - 2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 7668–7672, 2021.

[42] P. Wang, A. Yang, R. Men, J. Lin, S. Bai, Z. Li, J. Ma, C. Zhou, J. Zhou, and H. Yang. OFA: unifying architectures, tasks, and modalities through a simple sequence-to-sequence learning framework. In K. Chaudhuri, S. Jegelka, L. Song, C. Szepesvári, G. Niu, and S. Sabato, editors, *International Conference on Machine Learning, ICML 2022, 17-23 July 2022, Baltimore, Maryland, USA*, volume 162 of *Proceedings of Machine Learning Research*, pages 23318–23340. PMLR, 2022.

[43] W. Wang, H. Bao, L. Dong, J. Bjorck, Z. Peng, Q. Liu, K. Aggarwal, O. K. Mohammed, S. Singhal, S. Som, and F. Wei. Image as a foreign language: Beit pretraining for all vision and vision-language tasks. *CoRR*, abs/2208.10442, 2022.

[44] E. Wijmans, S. Datta, O. Maksymets, A. Das, G. Gkioxari, S. Lee, I. Essa, D. Parikh, and D. Batra. Embodied question answering in photorealistic environments with point cloud perception. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6659–6668, 2019.

[45] Z. Xu, Y. Shen, and L. Huang. Multiinstruct: Improving multi-modal zero-shot learning via instruction tuning, 2022.

[46] C. Yu, J. Wang, C. Peng, C. Gao, G. Yu, and N. Sang. Bisenet: Bilateral segmentation network for real-time semantic segmentation. In *Proceedings of the European conference on computer vision (ECCV)*, pages 325–341, 2018.

[47] Y. Zhang and J. Chai. Hierarchical task learning from language instructions with unified transformers and self-monitoring. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 4202–4213, Online, Aug. 2021. Association for Computational Linguistics.

[48] K. Zheng, K. Zhou, J. Gu, Y. Fan, J. Wang, Z. Li, X. He, and X. E. Wang. Jarvis: A neuro-symbolic commonsense reasoning framework for conversational embodied agents. *arXiv preprint arXiv:2208.13266*, 2022.

[49] B. Zhou, H. Zhao, X. Puig, S. Fidler, A. Barriuso, and A. Torralba. Scene parsing through ade20k dataset. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, July 2017.