ASC me to Do Anything: Multi-task Training for Embodied AI

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Abstract

Embodied AI has seen steady progress across a diverse set of independent tasks. While these varied tasks have different end goals, the basic skills required to complete them successfully overlap significantly. In this paper, our goal is to leverage these shared skills to learn to perform multiple tasks jointly. We propose Atomic Skill Completion (ASC), an approach for multi-task training for Embodied AI, where a set of atomic skills shared across multiple tasks are composed together to perform the tasks. The key to the success of this approach is a pre-training scheme that decouples learning of the skills from the high-level tasks making joint training effective. We use ASC to train agents within the AI2-TOR environment to perform four interactive tasks jointly, and find it to be remarkably effective. In a multi-task setting, ASC improves success rates by a factor of 2x on Seen scenes and 4x on Unseen scenes compared to no pre-training. Importantly, ASC enables us to train a multi-task agent that has a 52% higher Success Rate than training 4 independent single task agents. Finally, our hierarchical agents are more interpretable than traditional black box architectures.

1. Introduction

Embodied AI (E-AI) researchers have long sought to develop agents that can perform complex tasks within visual environments – tasks that require navigating around an environment [1, 5], interacting [4, 59, 66, 72, 74] and manipulating [14, 71] with objects that lie within it, following instructions [2, 60] and engaging with other agents [27, 28] or humans via QA [10, 24]. While steady progress has been made towards this ambitious goal, particularly in simulated worlds [19, 33, 54, 59, 71], most work today focuses on training agents to perform a single task.

Evidence across this large body of research suggests that: (a) Present day learning algorithms are very inefficient – perfecting simpler tasks such as point goal navigation can require more than a billion frames of experience [68], (b) The best performing methods are not as effective for long horizon tasks as well as tasks that involve rich interactions with the world and larger action spaces [66], and (c) As tasks get more complex, the generalization capability of these methods to unseen environments is quite poor [60]. How do we move towards developing effective multi-task E-AI agents, when training single task ones continues to be challenging?

In this paper, we propose an approach to jointly train multiple embodied tasks specified by natural language. Training these tasks directly is quite challenging. However, the compositional nature of natural language allows us to decompose the tasks into smaller easy-to-train parts that are shared across multiple tasks. For example, given two different tasks “put a plunger in cabinet.” and “what is the color of plunger?”, the agent must execute “find plunger” first, which is essentially an object navigation task. Our central idea is to pre-train such smaller tasks, referred to as atomic skills and later compose them to perform the more complex downstream task. More specifically, we pre-train a low-level skill executing policy on a set of atomic skills applicable to diverse downstream E-AI tasks. (4) Since high-level task invocation is now decoupled from low-level skill execution, the learning of high-level policies is hugely simplified, leading to the creation of effective multi-task embodied agents.

We pre-train our agent within the AI2-TOR environment with 110 object classes, 13 actions and continuous parameterization of the interaction skills. We consider 9 atomic skills common across a wide range of higher level
tasks. They range from navigation skills such as find X to interactive skills such as slice X and the answering skill answer. We then jointly train the agent to perform 4 challenging tasks (Figure 1) – (1) Short Horizon Instruction Following (SHIF), (2) Long Horizon Instruction Following (LHIF), (3) Interactive Question Answering (IQA) and (4) Exploratory Interaction (EXIN) and measure performance on Seen and Unseen environments. Given the interaction-heavy nature of these tasks, we consider two interaction modes – Standard whereby the agent must predict a bounding box that overlaps with the target object, and Hard which requires the agent to accurately predict a point within the object that it wishes to interact it.

Our results show that pre-training the agent via Asc leads to large improvements across all four tasks. In the Standard setting for multi-task training, Asc improves Success Rates (averaged across all tasks) from 15.1 → 41.9 for Seen and 4.3 → 16.2 for Unseen; in the Hard setting, the improvements are as dramatic – from 20.3 → 39.8 for Seen and 4.0 → 19.3 for Unseen. In the absence of pre-training, multi-task training results in a drop as compared to single task training.

2. Related Work

Multi-task learning. An ultimate goal of AI research is to build systems that can perform multiple tasks simultaneously. There are several previous works in computer vision [15,32,37,42,45,53,58], natural language understanding [8,9,31,38,39,43] and vision & language [25,26,30,40,50] domains that aim to handle multiple tasks simultaneously and address the issues that arise when tackling different tasks together. However, the visual embodied research works primarily focus only on a single specific task [10,68,69,74]. There are a few previous works that consider multi-task scenarios in the E-AI domain. For example, [7] transfer the knowledge of words and their grounding across two navigation tasks and [65] share parameters for language encoding and policy between two vision and language navigation tasks. Prior work in training multi-task agents is either operate in a grid-world environment [3], or environments with limited complexities, such as mine-craft to stack blocks [61] or ViZDoom with a single room including 5 objects [7]. We focus on long-horizon tasks that involve object interaction and state changes in addition to navigation. Furthermore, we show the effectiveness of pre-training of skills for learning different tasks jointly.

Pre-training. Pre-training strategies using supervised or unsupervised methods have proven to be effective in terms of learning efficiency and performance for downstream tasks in computer vision [20,21,41,62] and NLP [6,12,49,51]. Recently, pre-training methods have become popular in the E-AI domain. [13] jointly learn a policy and visual representations and show transfer to downstream navigation tasks. [68] propose a pre-training scenario that provides massive performance gains for the task of point navigation. [55,56] use mid-level tasks such as depth and room layout estimation for learning representations that enable fast and more gen-
eralizable learning of downstream tasks. [52, 64] have used contrastive predictive coding ideas to pre-train networks for downstream navigation tasks. [23] explore pre-training using auxiliary tasks. [36] learn skills for navigation via meta-reinforcement learning. Most of these works consider navigation as the downstream task. In contrast we consider tasks that involve object interaction. Moreover, we propose a pre-training strategy for a set of atomic skills that are composed in a hierarchical fashion.

**Hierarchical planning.** There is a rich history of hierarchical planning for performing different types of tasks [18, 22, 34, 35, 44]. Here, we mention a few approaches that are most relevant to ours. [11, 24] propose a hierarchical architecture for embodied question answering. [70] address the problem of sub-goal generation and finding a sequence of actions to reach the sub-goal. [29] use language as an abstraction to break down a complex task. [46] generate image sub-goals conditioned on an image goal and use the sub-goals for planning. [17] learn skills using intrinsic motivation to speed up learning downstream tasks that share a common structure. [63] address the problem of reusing knowledge from one task to another. [47] propose an analogy-making objective to generalize to unseen tasks and also a method for estimating the time-scale of sub-tasks. [16] address the problem of learning skills without a reward. These approaches have one or more of the following limitations: they do not train for multiple distinct tasks, they focus on simple tasks that do not require simultaneous navigation and object interaction, they use the same environment for train and test, or they do not consider high-dimensional visual input.

### 3. Problem Statement

An important goal of Embodied AI research is to develop agents that can perform a wide variety of diverse tasks. However, training multiple tasks at once is quite challenging since each task has a different success criteria, tasks often have different output structures, and training time becomes insurmountable. We propose pre-training agents on a shared set of skills that are core components of the target downstream tasks. As we show in our experiments, this improves training for complex interactive tasks and enables us to jointly train for multiple tasks.

**Skills.** The skills used to pre-train our agent are defined manually and correspond to semantically meaningful interactions with the environment that require very short sequences of primitive actions. We consider nine skills that involve navigation, interaction and answering questions. For example, go to and turn on are two example skills that we consider. These skills are part of a wide variety of interactive tasks.

**Tasks.** We consider four target tasks: (1) short-horizon instruction following; these tasks typically require a few skills (e.g., clean tomato, which requires putting the tomato in a sink and turning on the faucet). (2) long-horizon instruction following; these tasks span a longer horizon compared to short-horizon tasks and are inspired by the seven tasks defined in ALFRED [60], where only the high-level goal is available to the agent (as opposed to step-by-step instructions). An example is put the fork in the cup and move them to the kitchen counter. (3) interactive question answering, which is inspired by previous works of [10, 24]. The goal is to answer questions that require interaction with a scene. In this paper, the questions query the visual state or quantity of objects (e.g., Is the fridge open?, How many eggs are in the fridge?). (4) exploratory interaction; this task requires a long exploration phase until it finds the target object with which it needs to interact. This task shares similarities with the first two tasks, but it is more navigation-heavy compared to those. An example task is pickup the apple, which requires invoking the navigation skill multiple times (in case of failures) to reach the apple and then invoking the interaction skill pick up to pick up the apple.

**Environment.** We use AI2-THOR [33], a visually rich interactive framework, for performing our tasks. Following [60], no prior knowledge about the environment (e.g., a map) or additional sensors (e.g., depth cameras and GPS sensors) are available to the agent. We consider 110 object classes (37 of which are receptacle object classes) across 112 different indoor scenes. The environments provide multiple variations of each object class with different shapes, textures and colors.

**Agent.** To complete a task instance $T$, at each time step $t$, the agent observes an egocentric RGB image $v_t$ as input and takes action $a_t$, which can be a navigation action (e.g., move ahead, rotate right), an object interaction action (e.g., pick up, slice) or an answer action (e.g., yes, 3). The full list of actions is provided in the appendix. At each time step the agent also produces a coordinate $p = (x, y)$ on the image plane to indicate the object that will be interacted with. For instance, if the agent wishes to pick up a bowl, it issues the action pick up along with the coordinates of a pixel within the segment corresponding to the bowl. The agent’s objective is to learn a policy that can successfully complete task $T$. We consider a hierarchical policy $\pi_\theta$, which decomposes a task $T$ into multiple skills and dynamically selects sub-policies $\pi_{\theta^*}$ (corresponding to the desired skills) to execute.

**Continuous Interaction Parameterization.** A common practice for specifying target objects for interaction is to predict the target segmentation mask [60] or bounding box [24], then compare this to the ground truth segmentation masks provided by the simulator, select the interactable object with the most overlap and then use that as the target object. We name this setting Standard and also explore a more challenging continuous interaction parameterization, named Hard, a more realistic setting that no knowledge of the groundtruth is available to the agent. We interact with the environment...
by predicting a point \( p = (x, y) \) on the RGB image. If the point is on an object and the object is within the range of interaction, the agent can interact with the object. Otherwise, the interaction action will fail.

### 4. Multi-task Training

Given a task instance \( T \) specified by language, our agent predicts a sequence of skills and executes them to achieve the desired goal. Our aim is to train for multiple different tasks jointly. The tasks might have conflicting goals. For example, some tasks heavily rely on navigation within a scene, while others require long sequences of object interaction actions. Furthermore, the span of the tasks can vary significantly. Some tasks can be performed by executing a short sequence of actions, while others require a longer sequence. This imbalance makes joint training unstable. To tackle these challenges, we propose a hierarchical policy, which relies on a pre-training strategy for a set of skills. In this paper, we focus on instruction following, question answering, and exploration tasks, but our proposed framework is applicable to a larger set of tasks that can be specified using language and that can be accomplished using a shared set of skills.

We first present our hierarchical policy with continuous interaction parameterization, as shown in Fig. 2. Then, we describe the pre-training strategy for the skills. Finally, we describe how the various modules are combined and trained with a recovery planner.

#### 4.1. Hierarchical Policy

Our hierarchical policy, which we name Hierarchical Interactive Network (HINT), decomposes the task instance \( T \) into multiple sub-goals. Let \( v_t \) and \( a_t \) denote the observation and a primitive action (e.g., turn right) at time \( t \), respectively, and \( g_t = (s_t, o_t) \) denote a sub-goal, where \( s_t \) is the skill required to achieve the sub-goal \( g \) and \( o_t \) is the object required (if any) for that skill. The learning problem can be formulated as joint learning of a high-level policy \( \pi_\theta : (T, a_{t-1}, g_{t-1}, I_t) \rightarrow g_t \) parameterized by \( \theta \) and sub-policies \( \pi_{\theta^s} : (g_t, a_{t-1}, v_t) \rightarrow (a_t, p_t) \) parameterized by \( \theta^s \), where \( p_t \) is an interaction point on the image or \( \text{None} \) if the sub-policy does not require to interact with an object. For example, \( T \) can be “Heat potato”. One of the sub-goals, \( g_t \), will be “Open Microwave”, where \( g_{s_t} \) is the “Open” skill and \( g_{o_t} \) is “Microwave”. \( p_t \) should be a point on the microwave so the agent can interact with it.

**High-level Policy.** The high-level policy is implemented as a single layer Gated Recurrent Unit (GRU). Given the task instance \( T \), we first use a single layer GRU to extract the task embedding \( z^T \). We pass the current visual observation \( v_t \) into a pre-trained ResNet18, producing an encoded convolutional image feature \( z_{t}^{\text{img}} \in \mathbb{R}^{d \times w \times h} \), where \( d \) is the feature dimension, \( w \) and \( h \) is the size of convolutional feature map.

Besides the image feature and task feature, we also encode the last primitive action \( a_{t-1} \) and last sub-goal \( g_{t-1} = (s_{t-1}, o_{t-1}) \) into embeddings \( z_{t-1}^{\text{act}}, z_{t-1}^{\text{gs}} \) and \( z_{t-1}^{\text{go}} \) by linear projection. Following \([67]\), we use a multi-layer embedding network to encode \( [z_{t-1}^{T}, z_{t-1}^{\text{act}}, z_{t-1}^{\text{gs}}, z_{t-1}^{\text{go}}] \) into a compressed embedding \( z_t \in \mathbb{R}^d \). We further replicate \( z_t \) into \( \mathbb{R}^{d \times w \times h} \) and concatenate with \( z_{t}^{\text{img}} \). This information is reshaped into a 1-d vector and used to update the hidden states \( h_t \) of the GRU. The policy then produces a probability distribution over all the possible skills and target objects.

\[
g_{s_t}, g_{o_t} \sim \pi([z_t^{c}, z_{t}^{\text{img}}]) \tag{1}
\]

In recent hierarchical models (e.g., \([11]\)), the high-level policy typically updates its hidden states and sub-goals only when the previous sub-goal is finished or after a fixed number of steps. In contrast, our high-level policy updates its hidden states and the sub-goal after each primitive action.
is taken. This enables the high-level policy to observe the whole trajectory. The left panel of Figure 2 shows the high-level policy structure.

**Sub-Policies.** We have three distinct sub-policies in our experiments: navigation $\pi_{\text{nav}}$, interaction $\pi_{\text{act}}$ and question answering $\pi_{\text{qa}}$. The navigation and interaction sub-policies are distributions over primitive actions $a_t$. We concatenate the last primitive action embedding $z_{t-1}^{\text{act}}$ with sub-goal embedding sampled from the high-level policy $z_{t}^{\text{qa}}$, $z_{t}^{\text{img}}$ to generate $\hat{z}_{t}^{\text{img}}$:

$$a_t \sim \pi_{\text{nav/act}}([\hat{z}_{t}^{\text{img}}, z_{t}^{\text{img}}]),$$

where $z_{t}^{\text{img}}$ is the convolutional image feature from a separate ResNet18 network.

To interact with the target object $g_o$, the interaction sub-policy $\pi_{\text{act}}$ should point to a region of $g_o$, in the current observation. We treat the pointing process as an additional action to sample from the $\pi_{\text{act}}$. However, the action space for pointing is enormous – the number of pixels in the image are often 10000+ and training with this action space is infeasible. Therefore, we use a combination of discrete and continuous action parameterization to effectively represent the pointing action.

We first discretize the image into a $B \times B$ grid – which is a smaller action space – to obtain a rough estimate of the object location $\bar{p}$. Then, the discretization error can be recovered by sampling a continuous offset $\Delta p$ from a multivariate normal distribution with mean $\mu_p$ and variance $\nu$. We feed $\hat{z}_{t}^{\text{img}}$ into three $\{3 \times 3 \text{ Conv, BatchNorm, ReLU}, 3 \times 3 \text{ Conv, BatchNorm}\}$ blocks, producing the augmented feature $\hat{z}_{t}^{\text{aug}} \in \mathbb{R}^{d \times w \times h}$. We feed $\hat{z}_{t}^{\text{aug}}$ into three $1 \times 1$ Convs to produce the discrete location of the target point and the mean and the variance of multivariate normal distribution.

The target point can be estimated as $p = \bar{p} + \Delta p$:

$$\bar{p} \sim \pi_{p}^{\text{act}}(\hat{z}_{t}^{\text{aug}}), \quad \Delta p \sim \mathcal{N}(\mu_p, \nu)$$

For the question answering sub-policy, we use a standard VQA model that encodes the question with a single-layer GRU and performs dot product-based attention between the question encoding and the convolutional image feature. The answer can be sampled from the distribution produced by $\pi_{\text{qa}}$.

### 4.2. Skill Pre-training

Learning a general policy to perform multiple tasks jointly is quite challenging. Moreover, the common benchmarks for interactive tasks (e.g., ALFRED [60]) are typically small compared to passive, static tasks (e.g., ImageNet classification), which adds to the challenges of learning a generalizable model. One benefit of using a hierarchical policy is that the high-level policy can be disentangled from the skill sub-policies, which enables skill pre-training. In general, our definition of *skill* is meaningful interactions with minimal sequences of primitive actions.

Our skills span a range of activities such as navigation (e.g., $\langle \text{GoTo}, X \rangle$), interaction (e.g., $\langle \text{Open}, X \rangle$) and generating an answer (e.g., $\langle \text{Answer}, \text{None} \rangle$). The full list of skills, except the VQA skill, is shown in the header of Table 1. For interaction, we assume the agent is already close to the target thus requiring minimum primitive navigation. During pre-training, we put an agent into an environment and task the agent to complete atomic skills (e.g., GoTo Apple, Open Fridge, etc). We continuously sample plausible skill-object pairs and train the agent using the losses defined below. As an agent interacts with a scene, objects get pushed and moved around. As a result, we need to periodically reset and shuffle the environment after a fixed number of episodes.

We train the model with a combination of teacher forcing (TF), student forcing (SF) and Proximal Policy Optimization (PPO) [57] algorithms. For TF and SF, the expert trajectories can be obtained by the shortest path trajectory, which is obtained using a planner that has access to the full state of the environment. The loss for $\pi_{\text{nav/act}}$ (for TF and SF) is defined as:

$$\mathcal{L}_{\text{nav/act}} = \frac{1}{N} \sum_{t=1}^{N} \left[ \mathcal{L}_c(a_t, a^*_t) + \mathcal{L}_c(p_t, \bar{p}_t) + \mathcal{L}_g + L_{\text{aux}}^{\text{local}} + L_{\text{aux}}^{\text{local}} \right],$$

where $N$ is the number of steps, $\mathcal{L}_c$ is the cross-entropy loss, $\mathcal{L}_g$ is a weighted Gaussian log-likelihood loss for continuous policy gradient, and $a$ and $\bar{p}$ denote the primitive action and discretized interaction point. $a^*_t$ and $\bar{p}^*_t$ are the expert action at step $t$. Motivated by [73], we also add two auxiliary losses: $L_{\text{aux}}^{\text{local}}$ - penalty-reduced pixelwise logistic regression with focal loss and $L_{\text{aux}}^{\text{local}} - L_1$ loss for offset prediction over all the visible objects. More details about the loss functions are given in the appendix.

Training with PPO is challenging even for atomic skills, given the large space of actions and sparse reward setting. Hence, in addition to the goal success reward, we add a few auxiliary rewards to help the agent learn correct actions. More specifically, the reward vector is defined as $r = [r_{\text{success}}, r_{\text{visible}}, r_{\text{act}}, r_{\text{point}}]$ and the corresponding weights are defined in the appendix. In the reward vector, $r_{\text{success}} = 1$ if the sub-goal has achieved. $r_{\text{visible}} = 1$ if the target object is visible. $r_{\text{act}} = 1$ if the agent takes the correct primitive action (compared to the expert planner). $r_{\text{point}}$ is a 2-d Normal distribution where the mean is the ground truth point on the object. The agent can obtain partial rewards even if it is not successful in accomplishing the sub-goal. Note that $r_{\text{point}}$ will be equal to zero for skills that do not require object interaction. We find that these auxiliary rewards greatly benefit training with PPO.
4.3. Joint Multi-Task Training

The pre-training stage trains sub-policies to perform atomic skills in the environment but not how to communicate with the high-level policy to accomplish the tasks. We now train the high level policy and finetune the sub-policies jointly for multiple high-level tasks. The overall loss for the high-level policy $\pi_\theta$ and sub-policies $\pi_{gs}$ is defined as:

$$\mathcal{L} = \frac{1}{N} \sum_{t=1}^{N} [\mathcal{L}_c(g_{s_{t}}, g_{s_{t}}^*) + \mathcal{L}_c(g_{o_{t}}, g_{o_{t}}^*) + \mathbb{I}_{g_{s_{t}}} \mathcal{L}_{g_{s_{t}}}^{\otimes}],$$

(5)

where $\mathbb{I}_{g_{s_{t}}}$ is an indicator function and $\mathcal{L}_{g_{s_{t}}}^{\otimes}$ is the corresponding sub-policy loss for skill $g_{s_{t}}$.

We use a recovery planner to supervise the learning process of the high-level policy. This planner is defined as a dynamic planner for the high-level policy that can guide the agent to recover from any previous wrong actions. For example, for a given sub-goal “pick up apple”, the agent might pick up a nearby “orange” by mistake. The agent cannot pick up the apple unless the agent drops the orange first. During training, we monitor the expert plan for the sub-goal that is being executed and the actual action the agent took. If the agent performs a wrong interactive action, the recovery planner inserts a new sub-goal to reverse the effect of the previous wrong action. The ability to recover from failed actions is essential for high-level tasks, especially for long-horizon tasks. The use of a recovery planner is critical when training with student forcing.

During multi-task training, we randomly sample the episodes in proportion to the original task distribution and update the high-level policy and the corresponding sub-policies simultaneously. See appendix for more details on training the high level policy.

5. Experiments

Dataset. We train and evaluate our embodied agent within the AI2-THOR environment. We use 112 scenes across 4 scene types (kitchen, living rooms, bedrooms and bathrooms), and train our agent to complete four types of tasks – (1) short-horizon instruction following (StlFr), (2) long-horizon instruction following (LHIF), (3) interactive question answering (IQA), and (4) exploratory interaction (EXIN). All tasks require the agent to interact with objects in the environment. The variety of scenes (112), task types (4) and target object categories (110) make the dataset very challenging.

The dataset contains 42,037 episodes split into 33,487/1,391/1,358/3,217/2,584 for Training/Val-Seen/Val-Unseen/Test-Seen/Test-Unseen, respectively. At the start of each episode, the agent’s starting location is randomized and objects in a scene are automatically placed at random locations following a set of commonsense rules provided by AI2-THOR. Hence, no two episodes share the same configuration of objects. The Val-Seen and Test-Seen episodes are performed in the same scenes as Train (hence the suffix Seen), but the configurations of the agent and objects are novel. In the Unseen splits, both the environments and object configurations are new to the agent. Please refer to the appendix for dataset and tasks details – some crucial ones are presented below.

SHIF. These tasks are decomposed into a sequence of skills. E.g., “clean the apple” is decomposed into $\langle GoTo, Sink \rangle \rightarrow \langle Put, Sink \rangle \rightarrow \langle ToggleOn, Faucet \rangle \rightarrow \langle ToggleOff, Faucet \rangle \rightarrow \langle Pickup, Apple \rangle$. We initialize the episodes with fulfilled pre-conditions i.e. apple is already in hand in this example.

LHIF. We follow the setting of ALFRED [60] which consists of 7 different task types parameterized by 84 object classes. Crucially, we differ from ALFRED in that we only use the goal instruction and not the step-by-step details. This results in a significantly harder setting as also noted in [60].

IQA. For IQA, we follow the setting of the IQA dataset [24]. Given a question (e.g., “How many bottles are in the fridge?”), the agent needs to navigate to the fridge and open it to answer the question. There are three different question types – state questions, existence questions and counting questions, and the answer vocabulary is [Yes, No, 0, 1, 2, 3]. For each question type, we sample episodes with

| Model | Training | Goto seen/unseen | Pickup seen/unseen | Put seen/unseen | ToggleOn seen/unseen | ToggleOff seen/unseen | Open seen/unseen | Close seen/unseen | Slice seen/unseen |
|-------|----------|------------------|--------------------|----------------|----------------------|-----------------------|----------------|----------------|------------------|
| 1 Interact | TF | - | 8.3 | 5.0 | 25.0 | 20.0 | 54.2 | 41.9 | 53.5 | 36.2 |
| 2 Interact | SF | - | 16.7 | 10.0 | 29.9 | 19.4 | 66.7 | 49.6 | 53.6 | 49.6 |
| 3 Interact | MIX | - | 22.2 | 10.6 | 42.4 | 23.7 | 69.4 | 51.9 | 66.6 | 43.8 |
| 4 Navigate | TF | 32.6 | 18.4 | - | - | - | - | - | - |
| 5 Navigate | SF | 31.9 | 16.9 | - | - | - | - | - | - |
| 6 Navigate | MIX | 61.1 | 48.6 | - | - | - | - | - | - |
| 7 Joint | MIX | 47.9 | 25.6 | 22.9 | 11.9 | 40.3 | 30.6 | 72.2 | 57.5 | 74.3 | 47.5 | 59.7 | 41.2 | 71.5 | 54.4 | 44.4 | 22.5 |

Table 1. Skill Pre-training Results. Success Rates for Test-Seen and Test-Unseen at the 8 skills used in pre-training.
different scene configurations to make sure there is no bias that can be trivially exploited. EXIN. The EXIN task requires the agent to navigate to a target object, often very far away, and interact with it (e.g., pick up the apple, close the fridge, etc.). To create the episode, we randomly initialize the agent in the room and randomly sample a target object and skill. For object-state-change skills, we ensure that the target object’s state differs from its goal state. For skills that require additional objects as pre-conditions (e.g., “slice the apple” requires the knife in agent’s hand), the pre-condition is fulfilled at the beginning of the episode.

Evaluating Pre-training. Table 1 details performance at the 8 navigation and interaction atomic skills used for pre-training. We compare sub-policies trained with teacher forcing (TF), student forcing (SF) and a progression of TF → SF → reinforcement learning with PPO (MIX). We also compare training a joint sub-policy for all 8 skills vs 2 sub-policies, one for navigation (Navigate) and one for interaction (Interact) skills. We report the Success Rate on the test-seen and test-unseen sets.

We observe that: (1) For many skills, TF → SF → PPO provides gains over TF and SF; in some cases the gains are very large (18.4 to 48.6 for GoTo – Row 4 vs Row 6). (2) Joint training improves over Interact (Row 3 vs Row 7) but it is much worse than Navigate (Row 6 vs Row 7) – likely because properties of the navigation skill (such as length) are vastly different from others. (3) Skills that require interacting with very small objects (PickUp often picks up objects such as a pencil or knife) tend to be very challenging, since the target object is difficult to pin point. (4) The skill Success rates in Seen and Unseen rooms are encouraging, given the challenging environment, and useful for downstream tasks. The 9th skill (providing an answer), not shown in Table 1, uses the last image from the expert policy. Here, we obtain an accuracy of 76.0 on Seen and 52.5 on Unseen scenes.

Evaluating Multi-task Training. Table 2 details Success Rates in the Test scenes of several single and multi-task agents at the 4 tasks and also reports averages across all 4, separated by the Seen and Unseen splits. We report performance for 2 models: our proposed HINT and a baseline, FLAT – which is not hierarchical, and identical to our interactive sub-policy except the model takes task embedding instead of sub-goal embedding as input. We train both models in a single and multi-task setup. Further, HINT is trained with and without ASC pre-training in the Standard and Hard interactive settings. When trained without ASC, the sub-policy is initialized from scratch.

Given the large set of results, we refer to the Averages columns in the text below but encourage the reader to look at all columns in Table 2. We observe that: (1) Pre-training the agent with ASC provides very large gains across all 4 tasks when compared to no pre-training. For the multi-task training setup, these large gains are seen for both Standard (Row 2 vs Row 4) and Hard (Row 6 vs Row 8) settings. The Average columns show that the improvements are on the order of 2x for Seen and 4x for Unseen scenes. (2) ASC enables us to train effective multi-task agents. In the absence of pre-training, multi-task training results in a drop over single task training (Row 6 vs Row 5), but with ASC, we see gains in going to multi-task (Row 8 vs Row 7). (3) Our agent performs comparably well in the Hard setting (Row 4 vs Row 8) indicating that the network is effective at localizing points on target objects. (4) HINT outperforms FLAT by huge margins (Row 8 vs Row 10).

Ablation Study. Table 3 presents an ablation study. We ablate the effects of student forcing, random initialization of scenes, usage of the recovery planner and pre-training with ASC. As seen, removing each of these components provides a drop in the Seen and Unseen success rates on

| Interaction | Pretrain | Train | ShIF Seen | ShIF Unseen | LhIF Seen | LhIF Unseen | IQA Seen | IQA Unseen | EXIN Seen | EXIN Unseen | Averages Seen | Averages Unseen |
|-------------|----------|-------|-----------|-------------|-----------|-------------|---------|------------|-----------|-------------|---------------|---------------|
| **Model: Hierarchical Interactive Network (HINT)** |
| **Standard** | No | 1 Single | 75.9 | 7.1 | 5.1 | 0.1 | 45.8 | 12.8 | 21.6 | 8.1 | 37.0 | 7.0 |
| | No | 2 Multi | 42.4 | 3.0 | 2.8 | 0.0 | 14.6 | 14.4 | 0.8 | 0.0 | 15.1 | 4.3 |
| Uses Detector | Yes | 3 Single | 77.4 | 25.7 | 10.5 | 0.8 | 46.2 | 18.0 | 16.9 | 5.2 | 37.7 | 12.4 |
| | Yes | 4 Multi | 72.3 | 29.8 | 9.4 | 1.3 | 55.0 | 20.3 | 31.2 | 13.6 | 41.9 | 16.2 |
| **Hard** | No | 5 Single | 83.1 | 2.1 | 1.1 | 0.1 | 45.3 | 12.9 | 12.7 | 4.8 | 35.6 | 5.0 |
| | No | 6 Multi | 38.4 | 1.3 | 0.1 | 0.1 | 42.5 | 14.4 | 0.4 | 0.0 | 20.3 | 4.0 |
| Predicts Point | Yes | 7 Single | 80.8 | 20.0 | 6.0 | 0.3 | 46.4 | 17.9 | 14.1 | 5.7 | 36.8 | 10.9 |
| | Yes | 8 Multi | 71.7 | 42.7 | 5.4 | 0.6 | 55.4 | 22.3 | 26.7 | 11.4 | 39.8 | 19.3 |
| **Model: Flat** |
| **Hard** | No | 9 Single | 1.0 | 0.0 | 0.7 | 0.0 | 14.2 | 9.2 | 1.9 | 0.8 | 4.5 | 2.5 |
| | No | 10 Multi | 22.5 | 0.5 | 0.3 | 0.0 | 11.9 | 6.7 | 0.4 | 0.0 | 8.8 | 1.8 |

Table 2. Multi-task Results. Success Rates for Test-Seen and Test-Unseen for the 4 tasks. We evaluate 2 models, in single and multi-task settings in 2 interaction modes and also compare ASC pre-training to no-pretraining. Average metrics across all 4 tasks are also reported.
average across all four tasks. The largest drop is observed if pre-training is switched off indicating the immense benefit of pre-training. Random initialization is expectedly useful for generalization.

**Interpretability.** Figure 3 shows trajectories for Val-Seen episodes in the Hard interaction setting for each of the four task types. As observed, our hierarchical agent is able to solve them effectively. Importantly, our method is more interpretable than past approaches that directly output an action based on the current observation and the language specification of the task (e.g., [48]). At each time step, one can observe the sub-goals and pixel locations output by the high level policy. The sub-goals allow us to interpret the progress of the agent along its episode and its current sub-goal of interest, and the pixel heatmaps and object types allow us to interpret which object the agent is presently interested in interacting with, and where it thinks the object resides in the scene. For instance, in (b) one can notice sub-goals like *Pick up towel* and *Put sink* that are correctly executed. Also notice an error in (d) where the high level policy confuses a ball by the desk lamp, but the agent eventually recovers to find the correct desk lamp and then switch it on.

6. Conclusion

Solving Embodied AI tasks requires tackling unique challenges due to the long-horizon nature of the tasks, partial observability of the states and high-dimensional inputs such as images. While there has been significant progress in multi-task training in vision and NLP, less progress has been seen in Embodied AI, where models usually target an individual task. As a step towards multi-task training for Embodied AI, we propose Asc, a method that proves effective in training multiple tasks jointly. A key element of this approach is a pre-training strategy and a training regime for handling multiple embodied tasks. Our experimental evaluations show that our multi-task training approach provides better results compared to training each task individually, while the amortized amount of data for each task is significantly lower.

**Limitations:** The proposed approach has certain limitations. We discuss a few important ones here. First, the pre-training strategy relies on supervision from the environment. While the use of simulated environments makes this plausible, pre-training skills using only self supervision is an interesting area of research that we will address in future work. Second, the set of skills are manually defined. Automatic learning of the required skills is an interesting area of research that we will address in future work. Second, the set of skills are manually defined. Automatic learning of the required skills is an interesting direction to explore. Finally, this work abstracts away a lot of challenges involved in physical robot interactions. Given the numerous challenges, even in simulation, transfer to the physical world will be considered in future work. Having said that, we have tried to minimize the assumptions that are only valid in simulation.

**Negative societal impact:** The scope of our contribu-
tions do not have a direct negative societal impact. Research in the Embodied AI domain might lead to creating robots that can be used for malicious applications. While important to consider, we do not posit any imminent concern given the numerous challenges that remain in our quest to build autonomous and intelligent agents.

References

[1] Peter Anderson, Angel X. Chang, Devendra Singh Chaplot, A. Dosovitskiy, Saurabh Gupta, V. Koltun, J. Kosecka, Jitendra Malik, R. Mottaghi, M. Savva, and A. Znamier. On evaluation of embodied navigation agents. arXiv, 2018. 1
[2] Peter Anderson, Qi Wu, Damien Teney, Jake Bruce, Mark Johnson, Niko Sanderhauf, Ian Reid, Stephen Gould, and Anton Van Den Hengel. Vision-language navigation: Interpreting visually-grounded navigation instructions in real environments. In CVPR, 2018. 1
[3] Jacob Andreas, Dan Klein, and Sergey Levine. Modular multitask reinforcement learning with policy mapping. In International Conference on Machine Learning, pages 166–175. PMLR, 2017. 2
[4] Dhruv Batra, Angel X Chang, Sonia Chernova, Andrew J Davison, Jia Deng, Vladlen Koltun, Sergey Levine, Jitendra Malik, Igor Mordatch, Roozbeh Mottaghi, Manolis Savva, and Hao Su. Rearrangement: A challenge for embodied ai. arXiv, 2020. 1
[5] Dhruv Batra, Aaron Gokaslan, Aniruddha Kembhavi, Oleksandr Maksymets, R. Mottaghi, M. Savva, A. Toshev, and Erik Wijmans. Objectnav revisited: On evaluation of embodied agents navigating to objects. arXiv, 2020. 1
[6] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. In NeurIPS, 2020. 2
[7] Devendra Singh Chaplot, Lisa Lee, Ruslan Salakhutdinov, Devi Parikh, and Dhruv Batra. Embodied multimodal multitask learning. In IJCAI, 2020. 2
[8] Kevin Clark, Minh-Thang Luong, Urvashi Khandelwal, Christopher D. Manning, and Quoc V. Le. BAM! born-again multi-task networks for natural language understanding. In ACL, 2019. 2
[9] Ronan Collobert and Jason Weston. A unified architecture for natural language processing: Deep neural networks with multitask learning. In ICML, 2008. 2
[10] Abhishek Das, Samyak Datta, Georgia Gkioxari, Stefan Lee, Devi Parikh, and Dhruv Batra. Embodied Question Answering. In CVPR, 2018. 1, 2, 3
[11] Abhishek Das, Georgia Gkioxari, Stefan Lee, Devi Parikh, and Dhruv Batra. Neural module control for embodied question answering. In CoRL, 2018. 3, 4
[12] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In NAACL, 2019. 2
[13] Yilun Du, Chuang Gan, and Phillip Isola. Curious representation learning for embodied intelligence. arXiv, 2021. 2
[14] Kiana Ehsani, Winson Han, Alvaro Herrasti, Eli VanderBilt, Luca Weihs, Eric Kolve, Aniruddha Kembhavi, and Roozbeh Mottaghi. ManipulaTHOR: A Framework for Visual Object Manipulation. In CVPR, 2021. 1
[15] David Eigen and Rob Fergus. Predicting depth, surface normals and semantic labels with a common multi-scale convolutional architecture. In ICCV, 2015. 2
[16] Benjamin Eysenbach, Abhishek Gupta, Julian Ibarz, and Sergey Levine. Diversity is all you need: Learning skills without a reward function. In ICLR, 2019. 3
[17] Carlos Florensa, Yan Duan, and Pieter Abbeel. Stochastic neural networks for hierarchical reinforcement learning. In ICLR, 2017. 3
[18] Ronan Fruit and Alessandro Lazaric. Exploration-Exploitation in MDPs with Options. In AISTATS, 2017. 3
[19] Chuang Gan, Jeremy Schwartz, S. Alter, Martin Schrimpf, James Traer, Julian De Freitas, J. Kubitilus, Abhishek Bhandwad, N. Haber, Megumi Sano, Kuno Kim, Elias Wang, Damian Mrowca, Michael Lingelbach, Aidan Curtis, Kevin T. Feigelsis, Daniel Bear, Dan Gutfriend, David Cox, J. DiCarlo, Josh H. McDermott, J. Tenenbaum, and D. Yamin. Threedworld: A platform for interactive multi-modal physical simulation. arXiv, 2020. 1
[20] Deepthi Ghiadiyaram, Du Tran, and Dhruv Mahajan. Large-scale weakly-supervised pre-training for video action recognition. In CVPR, 2019. 2
[21] Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. In CVPR, 2014. 2
[22] Sandeep Goel and Manfred Huber. Subgoal discovery for hierarchical reinforcement learning using learned policies. In FLAIRS conference, 2003. 3
[23] Daniel Gordon, Abhishek Kadian, Devi Parikh, Judy Hoffman, and Dhruv Batra. Splitnet: Sim2sim and task2task transfer for embodied visual navigation. In ICCV, 2019. 3
[24] Daniel Gordon, Aniruddha Kembhavi, Mohammad Rastegari, Joseph Redmon, Dieter Fox, and Ali Farhadi. Iqa: Visual question answering in interactive environments. In CVPR, 2018. 1, 3, 6
[25] Tanmay Gupta, Amita Kamath, Aniruddha Kembhavi, and Derek Hoiem. Towards general purpose vision systems. arXiv, 2021. 2
[26] Ronghang Hu and Amanpreet Singh. Transformer is all you need: Multimodal multitask learning with a unified transformer. arXiv, 2021. 2
[27] Unnat Jain, Luca Weihs, Eric Kolve, Ali Farhadi, Svetlana Lazebnik, Aniruddha Kembhavi, and Alexander G. Schwing. A cordial sync: Going beyond marginal policies for multi-agent embodied tasks. In ECCV, 2020. 1
[28] Unnat Jain, Luca Weihs, Eric Kolve, Mohammad Rastegari, Svetlana Lazebnik, Ali Farhadi, Alexander Schwing, and
Xiaodong Liu, Pengcheng He, Weizhu Chen, and Jianfeng Juncheng Li, Xin Wang, Siliang Tang, Haizhou Shi, Fei Wu, Hoang Le, Nan Jiang, Alekh Agarwal, Miroslav Dudík, Yiding Jiang, Shixiang Gu, Kevin Murphy, and Chelsea Finn. Ubernet: Training a universal convolutional neural network for low-, mid-, and high-level vision using diverse datasets and limited memory. In CVPR, 2017. 2

Eric Kolve, Roozbeh Mottaghi, Winson Han, Eli VanderBilt, Luca Weihs, Alvaro Herrasti, Daniel Gordon, Yuke Zhu, Abhinav Gupta, and Ali Farhadi. Ai2-thor: An interactive 3d environment for visual ai. arXiv, 2017. 1, 3

Tejas D Kulkarni, Karthik Narasimhan, Ardavan Saedi, and Josh Tenenbaum. Hierarchical deep reinforcement learning: Integrating temporal abstraction and intrinsic motivation. In NeurIPS, 2016. 3

Hoang Le, Nan Jiang, Alekh Agarwal, Miroslav Dudík, Yisong Yue, and Hal Daumé. Hierarchical imitation and reinforcement learning. In ICML, 2018. 3

Junhyuk Oh, Satinder Singh, Honglak Lee, and Pushmeet Kohli. Zero-shot task generalization with multi-task deep reinforcement learning. In ICML, 2017. 3

Alexander Pashevich, Cordelia Schmid, and Chen Sun. Episodic transformer for vision-and-language navigation. In ICCV, 2021. 8

Matthew E Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. Deep contextualized word representations. In NAACL, 2018. 2

Zhongzheng Ren and Yong Jae Lee. Cross-domain self-supervised multi-task feature learning using synthetic imagery. In CVPR, 2018. 2

Manolis Savva, Abhishek Kadian, Oleksandr Maksymets, Yili Zhao, Erik Wijmans, Bhavana Jain, JulianStraub, Jia Liu, VladlenKoltun, Jitendra Malik, Devi Parikh, and Dhruv Batra. Habitat: A platform for embodied ai research. In ICCV, 2019. 1

Alexander Sax, Bradley Emi, Amir R. Zamir, Leonidas J. Guibas, Silvio Savarese, and Jitendra Malik. Mid-level visual representations improve generalization and sample efficiency for learning visuomotor policies. In CoRL, 2019. 2

Alexander Sax, Jeffrey O. Zhang, Bradley Emi, Amir Zamir, Silvio Savarese, Leonidas Guibas, and Jitendra Malik. Learning to navigate using mid-level visual priors. In CoRL, 2020. 2

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. arXiv, 2017. 5

Ozan Sener and Vladlen Koltun. Multi-task learning as multi-objective optimization. In NeurIPS, 2018. 2

Bokui Shen, Fei Xia, Chengshu Li, Roberto Mart’ın-Mart’in, Linxi Fan, Guanzhi Wang, S. Buch, C. D’Arpino, Sanjana Srivastava, Lyne P. Tchapmi, M. Tchapmi, Kent Vainio, Li Fei-Fei, and S. Savarese. igibson, a simulation environment for interactive tasks in large realistic scenes. arXiv, 2020. 1

Mohit Shridhar, Jesse Thomason, Daniel Gordon, Yonatan Bisk, Winson Han, Roozbeh Mottaghi, Luke Zettlemoyer, and Dieter Fox. Alfred: A benchmark for interpreting grounded instructions for everyday tasks. In CVPR, 2020. 1, 3, 5, 6

Tianmin Shu, Caiming Xiong, and Richard Socher. Hierarchical and interpretable skill acquisition in multi-task reinforcement learning. arXiv preprint arXiv:1712.07294, 2017. 2
We periodically reset and randomly initialize the objects in the room every 10 rollout steps. We use Adam with learning rate of $3 \cdot 10^{-4}$, and train with teacher forcing (20M steps), student forcing (20M steps) and proximal policy optimization (60M steps). For student forcing, the agent alternates between choosing actions from ground-truth planner or from the current learned policy with some probability $\epsilon$. We use a linear decay schedule ($\epsilon = 1.0 \rightarrow 0.0$) in our experiment. The corresponding weight for the reward vector $r = [r_{\text{success}}, r_{\text{visible}}, r_{\text{act}}, r_{\text{point}}]$ is $[20.0, 1.0, 1.0, 0.5]$. Our model can be trained with 8 Titan X GPU with 72 processes in 5 days.

**Stage 2: Multi-Task Training.** For multi-task training, we initialize the sub-policies with the pre-trained model. We use the same ResNet18 model pre-trained on ImageNet as the backbone, and all residual blocks in the backbone are fixed during training. We use Adam with learning rate of $3\times 10^{-4}$ to train the high-level policy and $3\times 10^{-5}$ to finetune the sub-policies. For long horizon tasks such as LTLH, it is very hard to successfully accomplish the task by random exploration of the environment. Thus we only train with teacher forcing and student forcing and do not use PPO. For all models, we train with teacher forcing (10M steps) and student forcing (10M steps). Similar to skill pre-training, we use a linear decay schedule ($\epsilon = 1.0 \rightarrow 0.6$) in our experiment. For multi-task training, our model can be trained with 8 Titan X GPU with 40 processes in 2 days.

**Appendix**

**A. Implementation Details**

Here we provide the implementation details of our full model. There are two stages: **Stage 1: Skill Pre-training.** For interaction, navigation and question answering sub-policies, we use a ResNet18 model pre-trained on ImageNet as the backbone. The first two residual blocks in the backbone are fixed during training. We periodically reset and randomly initialize the objects in the room every 10 rollout steps. We use Adam with learning rate of $3 \cdot 10^{-4}$, and train with teacher forcing (20M steps), student forcing (20M steps) and proximal policy optimization (60M steps). For student forcing, the agent alternates between choosing actions from ground-truth planner or from the current learned policy with some probability $\epsilon$. We use a linear decay schedule ($\epsilon = 1.0 \rightarrow 0.0$) in our experiment. The corresponding weight for the reward vector $r = [r_{\text{success}}, r_{\text{visible}}, r_{\text{act}}, r_{\text{point}}]$ is $[20.0, 1.0, 1.0, 0.5]$. Our model can be trained with 8 Titan X GPU with 72 processes in 5 days.

**Stage 2: Multi-Task Training.** For multi-task training, we initialize the sub-policies with the pre-trained model. We use the same ResNet18 model pre-trained on ImageNet as the backbone, and all residual blocks in the backbone are fixed during training. We use Adam with learning rate of $3\times 10^{-4}$ to train the high-level policy and $3\times 10^{-5}$ to finetune the sub-policies. For long horizon tasks such as LTLH, it is very hard to successfully accomplish the task by random exploration of the environment. Thus we only train with teacher forcing and student forcing and do not use PPO. For all models, we train with teacher forcing (10M steps) and student forcing (10M steps). Similar to skill pre-training, we use a linear decay schedule ($\epsilon = 1.0 \rightarrow 0.6$) in our experiment. For multi-task training, our model can be trained with 8 Titan X GPU with 40 processes in 2 days.

**B. Action Space**

Here we provide the details of our action space: **High-level policy.** Our high-level policy predicts the skills and target object type for the sub-policies. There are 10 skills including $\langle \text{End} \rangle$ (indicating the end of the execution) and 110 target objects. The skills are $\langle \text{Goto} \rangle$, $\langle \text{Pickup} \rangle$, $\langle \text{Put} \rangle$, $\langle \text{ToggleOn} \rangle$, $\langle \text{ToggleOff} \rangle$, $\langle \text{Open} \rangle$, $\langle \text{Close} \rangle$, $\langle \text{Slice} \rangle$, $\langle \text{Answer} \rangle$ and $\langle \text{End} \rangle$. Since $\langle \text{Answer} \rangle$ and $\langle \text{End} \rangle$ do not take any target object, there are $8 \times 110 + 2 = 882$ possible choices at each time step for the high-level policy.

**Navigation sub-policy.** The agents navigate through the environment via 6 different actions $\langle \text{MoveAhead} \rangle$, $\langle \text{RotateLeft} \rangle$, $\langle \text{RotateRight} \rangle$, $\langle \text{LookUp} \rangle$, $\langle \text{LookDown} \rangle$ and $\langle \text{Done} \rangle$. 
Interaction sub-policy. For interaction sub-policy, we assume the agent is close to the target, thus needs to navigate and perform the interaction action. Thus the action space is MoveAhead, RotateLeft, RotateRight, LookUp, LookDown, OpenObject, CloseObject, PickupObject, PutObject, ToggleObjectOn, ToggleObjectOff, SliceObject and Done. For interactive actions, the interaction sub-policy also needs to predict an interaction point on the image plane which is specified by a discrete location on a grid and a continuous offset from the point on the grid. We consider an $8 \times 8$ grid, the continuous offset is sampled from a 2-d multivariate normal distribution.

Question answering sub-policy. The action space for question answering sub-policy is Yes, No, 0, 1, 2 and 3.

C. Auxiliary Loss Functions

We add two auxiliary losses during skill pre-training: $L_{\text{focal}}^{\text{aux}}$ and $L_{1}^{\text{aux}}$. Following [73], we smooth out all ground truth object centers $Y \in [0, 1]^{W \times H \times C}$ using a Gaussian kernel $Y_{xyc} = \exp(-(x-p_{x})^{2}+(y-p_{y})^{2})$, where $\sigma_{pc}$ is the standard deviation and depends on the object size. The training objective is penalty-reduced pixelwise logistic regression with focal loss:

$$L_{\text{focal}}^{\text{aux}} = \frac{1}{M} \sum_{xyc} \left\{ \begin{array}{ll}
(1 - Y_{xyc})^\alpha \log(\hat{Y}_{xyc}) & \text{if } Y_{xyc} = 1 \\
(1 - Y_{xyc}^\beta)(\hat{Y}_{xyc})^\alpha \log(1 - \hat{Y}_{xyc}) & \text{otherwise}
\end{array} \right.$$  

where $\alpha$ and $\beta$ are hyper-parameters of the focal loss ($\alpha = 2$, $\beta = 4$). $M$ is the number of object centers in image. The offset mean is shared across all classes and can be trained with an L1 loss:

$$L_{1}^{\text{aux}} = \frac{1}{M} \sum_{p} |\mu_{p} - \mu_{p}^*|,$$  \hspace{1cm} (6)

where $\mu_{p}$ is the predicted mean of the offset and $\mu_{p}^*$ is the target offset.

D. Results of task sub-categories

Table 2 shows the average performance. Here we show the detailed results for sub-categories of each task in Table 4, Table 5 and Table 6.

E. Dataset

We describe the details of our datasets as mentioned in Section 5 (line 289). Table 7 shows the text templates used to generate the instructions for different tasks. {obj}, {recep} and {mrecep} correspond to target object, receptacle and movable receptacle, respectively. Table 8 shows the splits for the four task types, including seen (novel configurations) and unseen (novel scenes) splits for validation and testing. Fig. 4 shows the distribution of sub-categories for each task type (3 for SHF and IQA and 7 for LHF and EXIN). In general, the distributions are balanced across sub-categories, but IQA has roughly twice the number of object state questions than for existence or counting. The reason is that there are various types of object states (open/closed, toggled on/off, dirty/clean, or empty/full).

In order to illustrate the richness in terms of target object types and receptacles in our datasets, Fig. 5 shows the respective distributions across all five splits in LHF and IQA. The other two tasks share a similar distribution.

F. More Qualitative Examples

Figs. 6, 7, 8, 9, and 10 show several validation seen trajectories for all four task types. We only include interaction actions (besides start and end observations) for all tasks.

Failures. Some of the included trajectories show failures that naturally and often occur across all task types and whose accumulation leads to the achieved success rates. Fig. 6 (“heat bread” and “clean cloth”) show a wrong target object for the pickup skill (plate instead of bread) issued by the high-level policy, which is recovered by the sub-policy, and failure to pickup an object with a small footprint in the given observation (cloth) by the sub-policy. Fig. 8 (“put a hot cup from microwave in dining table”) shows two failed interactions with a Cabinet. Fig. 9 (“is any soap bottle in or on the toilet?”) again shows a failed interaction, which is eventually rendered irrelevant since the answer in this episode could be provided by observing the object lying on the surface of the toilet. Fig. 11 shows trajectories for failed episodes, where interaction with small or partially occluded objects is a common failure mode.

G. Dataset Terms of Service

We use AI2-THOR to create our dataset which is under Apache License 2.0.
### Table 4. Short Horizon Instruction Following (SHIF) and Interactive QA (IQA) results.

| Interaction | Pretrain | Train | Heat | Clean | Cool | Averages | Existing | Counting | State | Averages |
|-------------|----------|-------|------|-------|------|----------|----------|----------|-------|----------|
|             |          |       | Seen | Unseen | Seen | Unseen | Seen | Unseen | Seen | Unseen | Seen | Unseen |
| **Model:** Hierarchical Interactive Network (HINT) |          |       |      |       |      |         |          |          |       |         |      |       |
| **Standard** | No       |       |      |       |      |         |          |          |       |         |      |       |
|             | 1 Single |       |      |       |      |         |          |          |       |         |      |       |
|             | 88.0     | 2.3   | 54.0 | 6.2   | 85.7 | 12.7    | 75.9     | 7.1      | 55.2 | 18.5    | 36.2 | 8.8    | 46.0 | 11.1   | 45.8 | 12.8   |
|             | 41.0     | 4.7   | 29.9 | 1.2   | 56.2 | 3.2     | 42.4     | 3.0      | 17.5 | 16.3    | 10.5 | 10.2   | 15.9 | 16.7   | 14.6 | 14.4   |
|             | 2 Multi  |       |      |       |      |         |          |          |       |         |      |       |
|             | 87.5     | 23.3  | 54.7 | 17.3  | 90.0 | 36.5    | 77.4     | 25.7     | 54.0 | 20.0    | 32.5 | 11.0   | 52.1 | 22.9   | 46.2 | 18.0   |
|             | 81.0     | 25.6  | 55.5 | 32.1  | 80.4 | 31.7    | 72.3     | 29.8     | 66.5 | 25.0    | 39.3 | 12.0   | 59.3 | 23.8   | 55.0 | 20.3   |
| Uses Detector | Yes     |       |      |       |      |         |          |          |       |         |      |       |
|             | 3 Single |       |      |       |      |         |          |          |       |         |      |       |
|             | 94.0     | 0.0   | 59.9 | 0.0   | 95.5 | 6.4     | 83.1     | 2.1      | 54.2 | 18.8    | 36.0 | 8.8    | 45.8 | 11.1   | 45.3 | 12.9   |
|             | 90.0     | 2.3   | 19.0 | 0.0   | 56.2 | 1.6     | 38.4     | 1.3      | 17.5 | 16.3    | 10.5 | 10.2   | 15.9 | 16.7   | 14.6 | 14.4   |
|             | 4 Multi  |       |      |       |      |         |          |          |       |         |      |       |
|             | 40.0     | 0.0   | 95.5 | 6.4   | 83.1 | 2.1     | 38.4     | 1.3      | 17.5 | 16.3    | 10.5 | 10.2   | 15.9 | 16.7   | 14.6 | 14.4   |
| **Hard**  | No       |       |      |       |      |         |          |          |       |         |      |       |
|             | 5 Single |       |      |       |      |         |          |          |       |         |      |       |
|             | 14.2     | 8.3   | 6.8  | 2.3   | 21.6 | 17.1    | 14.2     | 9.2      | 14.2 | 9.2     |      |       |
|             | 13.8     | 5.5   | 9.3  | 5.5   | 12.5 | 9.2     | 11.9     | 6.7      | 14.2 | 9.2     |      |       |
|             | 6 Multi  |       |      |       |      |         |          |          |       |         |      |       |
|             | 9.2      | 11.9  | 6.7  | 14.2  | 9.2   | 11.9    | 6.7      | 14.2     | 14.2 | 9.2     |      |       |
| Predicts Point | Yes  |       |      |       |      |         |          |          |       |         |      |       |
|             | 7 Single |       |      |       |      |         |          |          |       |         |      |       |
|             | 12.7     | 2.0   | 10.0 | 0.0   | 1.3  | 0.0     | 1.3      | 0.0      | 1.3  | 0.0     |      |       |
|             | 12.7     | 2.0   | 10.0 | 0.0   | 1.3  | 0.0     | 1.3      | 0.0      | 1.3  | 0.0     |      |       |
|             | 8 Multi  |       |      |       |      |         |          |          |       |         |      |       |
|             | 15.3     | 3.0   | 10.7 | 0.0   | 1.3  | 0.7     | 0.0      | 0.0      | 0.0  | 0.0     |      |       |
| **Model:** Flat |         |       |      |       |      |         |          |          |       |         |      |       |
| **Hard**  | No       |       |      |       |      |         |          |          |       |         |      |       |
|             | 9 Single |       |      |       |      |         |          |          |       |         |      |       |
|             | 2.0      | 0.0   | 2.7  | 0.0   | 0.0  | 0.0     | 0.0      | 0.0      | 0.0  | 0.0     |      |       |
|             | 2.0      | 0.0   | 2.7  | 0.0   | 0.0  | 0.0     | 0.0      | 0.0      | 0.0  | 0.0     |      |       |

Table 5. Long Horizon Instruction Following (LHIF) results.
Model: Hierarchical Interactive Network (HINT)

| Standard | No | Single | 11.0 | 6.7 | 0.0 | 0.0 | 11.1 | 6.7 | 38.9 | 20.0 | 22.0 | 0.0 | 27.8 | 6.67 | 40.0 | 16.7 | 21.6 | 8.1 |
|----------|----|--------|------|-----|-----|-----|------|-----|------|-----|-----|-----|------|-----|-----|-----|-----|----|
| Uses | Yes | Multi | 0.0  | 0.0 | 0.0 | 0.0 | 0.0  | 0.0 | 0.0  | 0.0 | 2.8 | 0.0  | 0.0  | 0.0 | 0.0  | 0.0 | 0.0  | 0.0 |
| Detector | No | Single | 5.6  | 6.7 | 11.1 | 0.0 | 27.8 | 6.7 | 30.6 | 6.7 | 13.9 | 6.7 | 19.4 | 10.0 | 10.0 | 0.0 | 16.9 | 5.2 |
| Predicts | Yes | Multi | 27.8 | 3.3 | 25.0 | 20.0 | 44.4 | 13.3 | 50.0 | 20.0 | 33.3 | 13.3 | 27.8 | 16.7 | 10.0 | 8.3 | 31.2 | 13.6 |
| Predicts | No | Single | 5.6  | 6.7 | 0.0  | 6.7 | 5.6  | 0.0 | 33.0 | 13.3 | 11.1 | 0.0 | 22.2 | 6.7  | 11.1 | 0.0 | 12.7 | 4.8 |
| Predicts | Yes | Multi | 0.0  | 0.0 | 0.0  | 0.0 | 0.0  | 0.0 | 0.0  | 0.0 | 2.8 | 0.0  | 0.0  | 0.0 | 0.0  | 0.0 | 0.0  | 0.0 |

Table 6. Exploratory Interaction (EXIN) Results.

Table 7. Instruction templates for SHiF, LHIF, IQA and EXIN.

Table 8. Dataset splits.
|            | train | valid seen | valid unseen | test seen | test unseen |
|------------|-------|------------|-------------|-----------|------------|
| **ShIF**   |       |            |             |           |            |
| clean      | 11.3  | 6.84       | 5.64        |           |            |
| heat       | 48    | 35         | 47          |           |            |
| cool       | 38    | 40         | 40          |           |            |
| **LHIF**   |       |            |             |           |            |
| pick and place with movable recip | 1303 | 1302 | 1301 | 1300 | 1300 |
| look at obj in light | 50 | 50 | 50 | 50 | 50 |
| pick clean then place in recip | 50 | 50 | 50 | 50 | 50 |
| pick heat then place in recip | 150 | 150 | 150 | 150 | 150 |
| pick two obj and place | 100 | 100 | 100 | 100 | 100 |
| pick and place simple | 43 | 43 | 43 | 43 | 43 |
| pick cool then place in recip | 924 | 924 | 924 | 924 | 924 |
| **ExIIn**  |       |            |             |           |            |
| PutObject  | 360   | 360       | 360         | 360       | 360       |
| SliceObject | 1805 | 1805     | 1805        | 1805      | 1805      |
| PickupObject | 2360 | 2360     | 2360        | 2360      | 2360      |
| ToggleObjectOff | 860 | 860 | 860 | 860 | 860 |
| OpenObject | 133   | 133       | 133         | 133       | 133       |
| ToggleObjectOn | 1955 | 1955     | 1955        | 1955      | 1955      |
| CloseObject | 2260 | 2260     | 2260        | 2260      | 2260      |

**Figure 4.** Distribution of task sub-categories across different splits.
Figure 5. **Target object and receptacle distributions** for LHF and IQA splits.
Figure 6. **Qualitative results of SHIF.** Valid-Seen trajectories for SHIF (part 1), including examples for heating and cleaning in kitchen and bathroom environments. For each example, we show the task instruction, the time step for each frame, overlaid interaction point heat maps for the interaction actions, invoked skill, and the target object for the current skill. Frames not shown correspond to navigation steps.
| Task: clean cloth | 0 | 48 | 50 | 52 | 54 | 56 |
|------------------|---|----|----|----|----|----|
| Start | Put | Toggle On | Toggle Off | Pickup | End |
| Sink | Faucet | Faucet | Cloth |

| Task: clean dishsponge | 0 | 10 | 12 | 14 | 16 | 18 |
|------------------------|---|----|----|----|----|----|
| Start | Put | Toggle On | Toggle Off | Pickup | End |
| Sink | Faucet | Faucet | DishSponge |

| Task: clean potato | 0 | 9 | 11 | 13 | 15 | 17 |
|-------------------|---|----|----|----|----|----|
| Start | Put | Toggle On | Toggle Off | Pickup | End |
| Sink | Faucet | Faucet | Potato |

| Task: cool pan | 0 | 30 | 32 | 34 | 36 | 38 | 40 | 42 |
|----------------|---|----|----|----|----|----|----|----|
| Start | Open | Put | Close | Open | Pickup | Close | End |
| Fridge | Fridge | Fridge | Fridge | Pan | Fridge |

| Task: cool tomato | 0 | 22 | 24 | 26 | 28 | 30 | 32 | 34 |
|-------------------|---|----|----|----|----|----|----|----|
| Start | Open | Put | Close | Open | Pickup | Close | End |
| Fridge | Fridge | Fridge | Fridge | Pot | Fridge |

Figure 7. **Qualitative results of SIIF.** Valid-Seen trajectories for SIIF (part 2), including examples for heating and cleaning in kitchen and bathroom environments. For each example, we show the task instruction, the time step for each frame, overlaid interaction point heat maps for the interaction actions, invoked skill, and the target object for the current skill. Frames not shown correspond to navigation steps.
Figure 8. **Qualitative results of LHF.** Valid-Seen trajectories for LHF, including examples for picking up, heating and placing on receptacle; as well as shorter tasks involving picking up and placing in receptacle or picking up and examining under (toggled on) light. The environments include kitchen, bedroom, and living room. For each task, we show the task instruction, the time step for each frame, overlaid interaction point heat maps for interactive actions, invoked skill, and the target object for the current skill. Frames not shown correspond to navigation steps.
Figure 9. **Qualitative results of IQA.** Valid-Seen trajectories for IQA, including examples for object state questions, existence and counting in bedrooms, living rooms, kitchens and bathrooms. For each example, we show the question, the time step for each frame, overlaid interaction point heat maps for interaction actions, invoked skill, and the target object for the current skill or the final answer. The two “is the bed dirty” examples show two different episode setups for the same question and target object states (note the different initialization). Frames not shown correspond to navigation steps.
Figure 10. **Qualitative results of EXIN.** Valid-Seen trajectories for EXIN, including examples for closing objects of several scales and placement of an object in a relatively small receptacle in living room, kitchen and bedroom environments. For each example, we show the task instruction, the time step for each frame, overlaid interaction point heat maps for interaction actions, the unique invoked skill, and the corresponding target object.
Figure 11. Failed episodes in validation-seen. (a) Picking up small objects like the *pencil* in this EXIN episode can lead to multiple failed interaction attempts. (b) The model produces its answer in IQA by looking at a *side table* instead of a *dining table*. (c) In this LHIF episode, the agent keeps exploring the upper part of the kitchen plan and never manages to reach the microwave. (d) Similar to (a), we observe a failed interaction with a small object like the *faucet* in a SHIF episode.