Reinforcement Learning for Sparse-Reward Object-Interaction Tasks in a First-person Simulated 3D Environment

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Abstract

Learning how to execute complex tasks involving multiple objects in a 3D world is challenging when there is no ground-truth information about the objects or any demonstration to learn from. When an agent only receives a signal from task-completion, this makes it challenging to learn the object-representations which support learning the correct object-interactions needed to complete the task. In this work, we formulate learning an attentive object dynamics model as a classification problem, using random object-images to define incorrect labels. We show empirically that this enables object-representation learning that captures an object's category (is it a toaster?), its properties (is it on?), and object-relations (is something inside of it?). With this, our core learner (a relational RL agent) receives the dense training signal it needs to rapidly learn object-interaction tasks. We demonstrate results in the 3D AI2Thor simulated kitchen environment with a range of challenging food preparation tasks. We compare our method’s performance to several related approaches and against the performance of an oracle: an agent that is supplied with ground-truth information about objects in the scene. We find that our agent achieves performance closest to the oracle in terms of both learning speed and maximum success rate.

1 Introduction

Consider a robotic home-aid agent that learns object-interaction tasks that involve using multiple objects together to accomplish various tasks such as chopping vegetables or heating meals. Such tasks are important for artificial intelligence (AI) to make progress on because of their large potential to impact our everday world: nursing robots can serve healthcare workers in hospitals, and home-aid robots can help busy families, the disabled, and the elderly.

Prior work on object-interaction tasks has focused on achieving strong training performance using expert demonstrations [Zhu et al., 2017; Shridhar et al., 2019]. Unfortunately, Zhu et al. [2017] found they were unable to learn relatively simple pick and place tasks when only learning from a sparse task-completion signal. Other work has relaxed the learning problem by relying on domain knowledge in the form of shaped rewards or object-affordance knowledge [Jain et al., 2019; Gordon et al., 2018].

Unfortunately, expert demonstrations and shaped rewards can be challenging to obtain for tasks novel to an agent. Additionally, it can be tedious or impossible to obtain ground-truth information about all novel objects an agent may encounter. Ideally, agents are capable of learning object-interaction tasks without this information. To work towards this, we focus on the setting where none of these are available.

Learning object-interaction tasks without expert demonstrations or shaped rewards is challenging because selecting between object-interactions induces a branching factor that scales with the number of visible objects, leading the agent choose from 50-100 actions at a given time-step. This leads the agent to infrequently experience a successful episode. When the agent does, task completion typically occurs after many hundred time-steps. Consider learning to toast bread. The agent should learn to turn on the toaster after a bread slice is placed inside, i.e. it needs to learn to represent containment relationships (the bread is inside the toaster) and object properties (the toaster is on or off). Without domain knowledge about objects, task-completion alone provides a weak learning signal for learning both to represent 3D object categories, properties, and relationships. When episodes last for hundreds of time-steps and the agent interacts with many objects, this makes it challenging to learn about how the agent’s object-interactions led to reward.

In this work, we find that we can achieve strong training performance on object-interaction tasks without expert demonstrations, shaped rewards, or ground-truth object-knowledge by incorporating inter-object attention and an object-centric model into a reinforcement learning agent. We call our agent the Learning Object Attention & Dynamics (or LOAD) agent. LOAD is composed of a base object-centric relational policy (Attentive Object-\textit{DQN}, §4.1) that leverages inter-object attention to incorporate object-relationships when estimating object-interaction action-values. Without ground-truth information to identify object categories, properties, or relationships, LOAD learns object-representations with a novel learning objective that frames learning an object-model as a classification problem, where random object-embeddings are
In order to study object-interaction tasks and evaluate our agent, we adopt the virtual home-environment AI2Thor [Kolve et al., 2017] (or Thor). Thor is an open-source environment that is high-fidelity, 3D, partially observable, and enables object-interactions. We show that LOAD is able to significantly reduce sample complexity in this domain where no prior work has yet learned sparse-reward object-interaction tasks without expert demonstrations or shaped rewards.

In our main evaluation, we compare pairing Attentive Object-DQN with our Attentive Object-Model to alternative representation learning methods, and show that learning with our object-model best closes the performance gap to an agent supplied with ground-truth information about object categories, properties, and relationships (§5.1). Through an analysis of the learned object-representations and inter-object attention learned by each auxiliary task, we provide quantitative evidence that our Attentive Object-Model best learns representations that capture the ground-truth information present in our oracle (§5.2). We hypothesize that this is the source of our strong performance. Afterwards, we perform a series of ablations to study the importance of object-representations which capture object-proprieties and object-relations for reducing sample-complexity (§5.3).

In summary, the key contributions of our proposal are: (1) LOAD: an RL agent that demonstrates how to learn sparse-reward object-interaction tasks with first-person vision without expert demonstrations, shaped rewards, or ground-truth object-knowledge. (2) A novel Attentive Object-Model auxiliary task, which frames learning an object-model as a classification problem. With our analysis, we provide evidence that for our 3D, high-fidelity domain and our architecture, it is key to learn object-representations which not only capture object-categories but also object-proprieties and object-relations.

2 Related Work

Learning object-interaction tasks in 3D, first-person environments. Due to the large branching factor induced by object-interactions, most work here has relied extensively on expert demonstrations [Zhu et al., 2017; Shridhar et al., 2019; Xu et al., 2019] or avoided this problem by hard-coding object-selection [Jain et al., 2019; Gordon et al., 2018]. The work most closely related to ours is Oh et al. [2017] (in Minecraft) and Zhu et al. [2017] (in Thor). Both develop a hierarchical reinforcement learning agent where a meta-controller provides goal object-interactions for a low-level controller to complete using ground-truth object-information. Both provide agents with knowledge of all objects and both assume lower-level policies pretrained to navigate to objects and to select interactions with a desired object. In contrast, we do not provide the agent with any ground-truth object information; nor do we pretrain navigation to objects or selection of them.

Object-Centric Relational RL. An intuitive approach to tasks with objects is object-centric relational RL. Most work here has used hand-designed representations of objects and their relations, showing things like improved sample-efficiency [Xu et al., 2020], improved policy quality [Zaragoza et al., 2010], and generalization to unseen objects [Van Hooft et al., 2015]. In contrast, we seek to learn object-representations and object-relations implicitly with our network. Most similar to our work is Zambaldi et al. [2018]—which applies attention to the feature vector outputs of a CNN. In this work, Attentive Object-DQN is a novel architecture extension for a setting with an object-centric observation- and action-space. Additionally, we show that learning an object-model as an auxiliary task can help drive learning of attention.

Learning an object-model as an auxiliary task. Most prior work here has focused on how an object-model can be used in model-based reinforcement learning by enabling superior planning [Ye et al., 2020; Veerapaneni et al., 2020; Watters et al., 2019]. In contrast, we do not use our object-model for planning and instead show that it can be leveraged to learn object-representation and inter-object attention to support faster policy learning in a model-free setting. Additionally, other work focused on domains where representation-learning only had to differentiate object-categories. We show that our method can additionally differentiate object-properties and does so significantly better than the object-model of Watters et al. [2019]. Our attentive object-model is most similar to the Contrastive Structured World Model (CSWM) [Kipf et al., 2019], which uses a maximum margin contrastive learning objective [Hadsell et al., 2006] to learn an object-model. Instead, we formulate a novel object-model contrastive objective as learning a classification problem. We note that they applied their model towards video-prediction and not reinforcement learning.

3 Sparse-Reward Object-Interaction Tasks in a First-Person Simulated 3D environment

Observations. We focus on an agent that has a 2D camera for experiencing egocentric observations $x^{ego}$ of the environment. Our agent also has a pretrained vision system that enables it to extract bounding box image-patches corresponding to the visible objects in its observation $X^{o} = \{x^{o,i}\}$. Besides boxes around objects, no other information is extracted (i.e., no labels, identifiers, poses, etc.). We assume the agent has access to its $(x, y, z)$ location and body rotation ($\varphi_1, \varphi_2, \varphi_3$) in a global coordinate frame, $x^{loc} = (x, y, z, \varphi_1, \varphi_2, \varphi_3)$.

Actions. In this work, we focus on the Thor environment. Here, the agent has 8 base object-interactions: $I = \{\text{Pickup}, \text{Put}, \text{Open}, \text{Close}, \text{Turn on}, \text{Turn off}, \text{Slice}, \text{Fill}\}$. The agent interacts with objects by selecting (object-image-patch, interaction) pairs $a = (b, x^{o,c}) \in I \times X^{o}$, where $x^{o,c}$ corresponds to the chosen image-patch. For example, the agent can turn on the stove by selecting the image-patch containing the stove-knob and the Turn on interaction (see Figure 2 for a diagram). Each action is available at every time-step and can be applied to all objects (i.e., no affordance information is given/used). Interactions occur over one time-step, though their effect may occur over multiple. For the example above, when the agent applies “Turn on” to the stove knob, food on the stove will
to take several time-steps to heat.

In addition to object-interactions, the agent can select from 8 base navigation actions: $A_X = \{\text{Move ahead, Move back, Move right, Move left, Look up, Look down, Rotate right, Rotate left}\}$. With \{Look up, Look down\}, the agent can rotate its head up or down in increments of $30^\circ$ between angles $\{0^\circ, \pm 30^\circ, \pm 60^\circ\}$. $0^\circ$ represents looking straight ahead. With \{Rotate Left, Rotate Right\}, the agent can rotate its body by $\{\pm 90^\circ\}$.

**Tasks.** We construct 8 tasks with the following 4 challenges. Challenge (A): the visual complexity of task objects (e.g. the cup is translucent). Challenge (B): the number of objects to be interacted with (e.g., “Slice Apple, Potato, Lettuce” requires the agent interact with 4 objects). Challenge (C): whether object-containment must be recognized and used (e.g. toasting bread in a toaster). Challenge (D): whether object-properties change (e.g. bread get’s cooked). See Figure 1 for a description of the challenges associated with each task and Figure 1 for example panels of 2 tasks.

**Reward.** We consider a single-task setting where the agent receives a terminal reward of $1$ upon task-completion.

### 4 LOAD: Learning Object Attention & Dynamics Agent

LOAD is a reinforcement learning agent composed of an object-centric relational policy, Attentive Object-DQN, and an Attentive Object-Model. LOAD uses 2 perceptual modules. The first, $f_{\text{enc}}$, takes in an observation $x$ and produces object-encodings $\{z_{o,i}\}_{i=1}^n$ for the $n$ visible object-image-patches $X^o = \{x_{o,i}\}_{i=1}^n$, where $z_{o,i} \in \mathbb{R}^d$. The second, $f_{\text{enc}}^{\text{ego}}$, takes in the egocentric observation and location $x^\kappa = [x^{\kappa,o}, x^{\kappa,\kappa}]$ to produce the context for the objects $z^\kappa \in \mathbb{R}^d$. LOAD treats state as the union of these variables: $s = \{z_{o,i}\} \cup \{z^\kappa\}$. Given object encodings, Attentive Object-DQN computes action-values $Q(s,a = \{b, x^{\kappa,i}\})$ for interacting with an object $x^{\kappa,i}$ and leverages an attention module $A$ to incorporate information about other objects $x^{\kappa,j}\neq i$ into this computation (see §4.1).

To address the representation learning challenge induced by a sparse-reward signal, object-representations $z_{o,i}$ and object-attention $A$ are trained to predict object-dynamics with an attentive object-model (see §4.2). See Figure 2 for an overview of the full architecture.

#### 4.1 Attentive Object-DQN

Attentive Object-DQN uses $\tilde{Q}(s,a)$ to estimate the action-value function $Q^\pi(s,a) = \mathbb{E}_\pi[\sum_{t=0}^\infty \gamma^t r_t | S_t = s, A_t = a]$, which maps state-action pairs to the expected return on starting from that state-action pair and following policy $\pi$ thereafter.

**Leveraging inter-object attention during action-value estimation.** In many tasks, an agent must integrate information about multiple objects when estimating $Q$-values. For example, in the “toast bread” task, the agent needs to integrate information about the toaster and the bread when deciding to turn on the toaster. To accomplish this, we exploit the object-centric observations-space and employ attention [Vaswani et al., 2017] to incorporate inter-object attention into $Q$-value estimation.

More formally, given an object-encoding $z_{o,i}^{\kappa}$, we can use attention to select relevant objects $A(z_{o,i}, Z^\kappa) \in \mathbb{R}^d$ for estimating $Q(s, a = \{b, x^{\kappa,i}\})$. With a matrix of object-encodings,
We store trajectories containing transitions where their dot-product determines whether a key is selected. To stabilize learning, we use Double-Q-learning [2016] to choose the next action: 

\[
\pi_t = \arg \max_a \hat{Q}(s_{t+1}, a; \theta).
\]

\[\hat{Q}(s, a = (b, x^{o,i})) = f_{\text{int}}([z^{o,i}, A(z^{o,i}, Z^{o}), z^K]) \]

Importantly, this enables us to compute Q-values for a variable number of unlabeled objects. We can similarly incorporate attention to compute Q-values for navigation actions by replacing \(Z^{o}W_q\) with \((W_q z^K)\) in equation 1. We estimate Q-values for navigation actions \(b \in A_N\) as follows:

\[
\hat{Q}(s, a = b) = f_{\text{nav}}([z^K, A(z^K, Z^K)]).
\]

Learning. We estimate \(\hat{Q}(s, a)\) as a Deep Q-Network (DQN) by minimizing the following temporal difference objective:

\[
\mathcal{L}_{\text{DQN}} = \mathbb{E}_{s_t, a_t, r_t, s_{t+1}} \left[ \|y_t - \hat{Q}(s_{t+1}, a_t; \theta)\|^2 \right],
\]

where \(y_t = r_t + \gamma \hat{Q}(s_{t+1}, a_{t+1}; \theta_{\text{old}})\) is the target Q-value, and \(\theta_{\text{old}}\) is an older copy of the parameters \(\theta\). To do so, we store trajectories containing transitions \((s_t, a_t, r_t, s_{t+1})\) in a replay buffer that we sample from Mnih et al. [2015]. To stabilize learning, we use Double-Q-learning Van Hasselt et al. [2016] to choose the next action: 

\[a_{t+1} = \arg \max_a \hat{Q}(s_{t+1}, a; \theta).\]

### 4.2 Attentive Object-Dynamics Model

Consider the global set of objects \(\{o^{i}_{t}\}_{i=1}^{m}\), where \(m\) is the number of objects in the environment. At each time-step, each object-image-patch the agent observes corresponds to a 2D projection of \(o^{i}_{t}, p(o^{i}_{t})\) (or \(p^{i}_{t}\) for short) and encodes it as \(z^{o,i}_{t}\). Given, an object-image-patch encoding \(z^{o,i}_{t}\) and a performed interaction \(a_t\), we can define an object-dynamics model \(D(Z^{o}_{t}, z^{o,i}_{t}, a_t)\) which produces the resultant encoding for \(p^{o,i}_{t+1}\). We want \(D(Z^{o}_{t}, z^{o,i}_{t}, a_t)\) to be closer to \(z^{o,i}_{t+1}\) than to encodings of other object-image-patches.

Classification problem. We can formalize this by setting up a classification problem. For an object-image-patch encoding \(z^{o,i}_{t}\), we define the prediction as the output of our object-dynamics model \(D(Z^{o}_{t}, z^{o,i}_{t}, a_t)\). We define the label as the encoding of a visible object-image-patch at the next time-step with the highest cosine similarity to the original encoding \(z^{o,i}_{t} = \arg \max_{z^{o,i}} \cos(z^{o,i}, z^{o,i}_{t+1})\). We then select \(K\) random object-encodings \(\{z^{o,i}_{k}\}_{k=1}^{K}\) as incorrect labels. Rewriting \(D(Z^{o}_{t}, z^{o,i}_{t}, a_t)\) as \(D\), this leads to:

\[
p(z^{o,i}_{t+1} | Z^{o}_{t}, a_t) = \frac{\exp(D^\top z^{o,i}_{t+1})}{\exp(D^\top z^{o,i}_{t+1}) + \sum_k \exp(D^\top z^{o,i}_{k})}. \quad (5)
\]

The set of indices corresponding to visible objects at time \(t\) is \(\nu_t = \{i : p^{o,i}_{t} \text{ is visible at time } t\}\). The set of observed object-image-patch encodings is then \(Z^{o}_{t} = \{z^{o,i}_{t}\} = \{z^{o,i}_{t+1}\}_{i \in \nu_t}\). Assuming the probability of each object’s next state is conditionally independent given the current set of objects and the action taken, we arrive at the following objective:

\[
\mathcal{L}_{\text{model}} = \mathbb{E}_{z_t, a_t, s_{t+1}} \left[ \sum_{i \in \nu_t} \log p(z^{o,i}_{t+1} | Z^{o}_{t}, a_t) \right] \quad (6)
\]

\[
\mathcal{L}_{\text{model}} = \mathbb{E}_{z_t, a_t, s_{t+1}} \left[ - \log p(Z^{o}_{t+1} | Z^{o}_{t}, a_t) \right]
\]

\[
\mathcal{L}_{\text{model}} = \mathbb{E}_{z_t, a_t, s_{t+1}} \left[ - \sum_{i \in \nu_t} \log p(z^{o,i}_{t+1} | Z^{o}_{t}, a_t) \right].
\]
Our final objective becomes:
\[ \mathcal{L} = \mathcal{L}_{\text{DQN}} + \beta_{\text{model}} \mathcal{L}_{\text{model}}. \] (7)

Leveraging inter-object attention for improved accuracy. Consider slicing an apple with a knife. When selecting “slice” on the apple patch, learning to attend to the knife patch both enables more accurate estimation of Q-values and higher model-prediction accuracy. We can accomplish this by incorporating \( A(z^{t,i}, Z^o) \) into our object-model as follows:
\[ D(Z^i_t, z^t_i, a_t) = f_{\text{model}}([z^{t,i}_t, A(z^{t,i}_t, Z^o_t), z^o_t]). \] (8)
To learn an action encoding \( z^o_t \) for action \( a_t \), following Oh et al. [2015]; Reed et al. [2014], we employ multiplicative interactions so our learned action representation \( z^o_t \) compactly models the cartesian product of all base actions \( b \) and object-image-patch selections \( o \) as
\[ z^o_t = W^o z^b_i \odot W^b b_t, \] (9)
where \( W^o \in \mathbb{R}^{d_a \times d_o} \), \( W^b \in \mathbb{R}^{d_a \times |A_t|} \), and \( \odot \) is an element-wise hadamard product. In practice, \( f_{\text{model}} \) is a small 1- or 2-layer neural network making this method compact and simple to implement.

5 Experiments

The primary aim of our experiments is to study how different auxiliary tasks for learning object-representations enable sample complexity comparable to an agent with oracle object-knowledge. We additionally study the degree to which each auxiliary task enables object-representation learning that captures the ground-truth knowledge present in our oracle agent. We conclude this section with ablation experiments studying the importance of different forms of object-knowledge in task learning.

Evaluation Settings. The agent’s spawning location is randomized from 81 grid positions. The agent receives a terminal reward of 1 if its task is completed successfully and 0 otherwise. It receives a time-step penalty of \(-0.04\). Episodes have a time-limit of 500 time-steps. The agent has a budget of \(500K\) samples to learn a task. This was the budget needed by a relational agent with oracle object-information.

Baseline methods for comparison. In order to study the effects of competing object-representation learning methods, we compare combining Attentive Object-DQN with the Attentive Object-Model against four baseline methods:
1. **Attentive Object-DQN.** This baseline has no auxiliary task and lets us study how well an agent can learn from the sparse-reward signal alone.
2. **Ground-Truth Object-Information.** This baseline has no auxiliary task. Instead, we supply the agent with 14 ground-truth features from the simulator. They roughly describe an object’s category (is it a toaster?), its properties (e.g., is it on/off/etc.?), and relevant object-containment (e.g., what object is this object inside of?). Please see §A.1 for detailed descriptions of these features.
3. **OCN.** The Object Contrastive Network [Pirk et al., 2019]. This method also employs a classification-like contrastive learning objective to cluster object-images across time-steps. However, it doesn’t use an object-model or incorporate action-information. This enforces us to study the importance of incorporating an object-model and action information.
4. **COBRA Object-Model.** This is the object-model employed by the COBRA RL agent [Watters et al., 2019]. They also targeted improved sample-efficiency—though in a simpler, fully-observable 2D environment with shapes that only needed differentiation by category. Their model had no mechanism for incorporating inter-object relations into its predictions.

To enable faster learning in a sparse-reward setting, all baselines sample training batches using a second self-imitation learning replay buffer of successful episodes [Oh et al., 2018].

5.1 Task Performance

Metrics. We evaluate agent performance by measuring the agent’s success rate over 5K frames every 25K frames of experience. The success rate is the proportion of episodes that the agent completes. We compute the mean and standard error of these values across 5 seeds. To study sample-efficiency, we compare each method to “Ground-Truth Object-Information” by computing what percent of the Ground-Truth Object-Information mean success rate AUC each method achieved.

We present sample-efficiency bar plots for all 8 of our tasks in Figure 3. We found that using containment relationships and recognizing changing object-properties (Challenges C & D in §3) were most indicative of task difficulty. We only present learning curve results for 4 tasks which match this criteria. We present all learning curves in Figure 6 in appendix §C. We additionally present the maximum success rate achieved by each method in Table 6 in appendix §C.1.

Performance. We find that using Ground-Truth Object-Information is able to get the highest success rate on all tasks. Attentive Object-DQN performs below all methods besides OCN on 7/8 tasks. Surprisingly, Attentive Object-DQN outperforms OCN on 5/8 tasks. OCN doesn’t incorporate action-information when learning to represent object-images across time-steps. We hypothesize that this leads it to learn degenerate object-representations that cannot discriminate object-properties that change due to actions, something important for our tasks.

In terms of sample-efficiency, our Attentive Object-Model comes closest to Ground-Truth Object-Information on 6/8 tasks. For tasks that require using objects together, such as “Fill Cup with Water” where a cup must be used in a sink or “Toast Bread Slice” where bread must be cooked in a toaster, our Attentive Object-Model significantly improves over the COBRA Object-Model. Interestingly, sample-efficiency goes above 100% on 2 tasks. We suspect that this is because the object-model provides a learning signal for inter-object attention which is not provided by oracle information.

5.2 Analysis of Learned Object Representations

In Table 2, we explore our conjecture that the key to strong task-learning performance is an agent’s ability to capture the information present in the oracle agent. To study this, we freeze the parameters of each encoding function, and add a linear layer to predict object-categories, object-properties, and containment relationships using a dataset of collected object-interactions we construct (see Appendix B.3 for details on the dataset and training). We find that our object-model best
Figure 3: Top-panel: we present the success rate over learning for competing auxiliary tasks. We seek a method that best enables our Attentive Object-DQN (grey) to obtain the sample-efficiency it would from adding Ground-Truth Object-Information (black). We visually see that LOAD (red) is best able to learn more quickly on tasks that require using containment-relationships (e.g. a cup in a sink) or recognizing changing object properties (e.g. a toaster turning on with bread in it).

Bottom-panel: by measuring the % AUC achieved by each agent w.r.t to the agent with ground-truth information, we can measure how close each method is to the performance of an agent with ground-truth object-knowledge. We find LOAD (red), which learns an attentive object-model best closes the performance gap on 6/8. We hypothesize that this is due to our object-model’s ability to capture oracle object-information about object-categories, object-properties, and object-relations. We show evidence for this in Table 2.

Table 2: Performance of different unsupervised learning methods for learning object-features (see §5.2 for details). We find that our object-model best captures features present in the oracle agent, providing evidence that its strong object-representation learning is responsible for its strong task-learning performance.

| Representation Learning Method | Category | Object-Properties | Containment Relationship |
|-------------------------------|----------|-------------------|-------------------------|
| OCN                           | 39.2 ± 8.2 | 66.5 ± 8.5 | 69.1 ± 9.5 |
| COBRA Object-Model            | 79.8 ± 2.8 | 73.4 ± 8.9 | 83.1 ± 5.8 |
| Attentive Object-Model        | 88.6 ± 3.5 | 98.6 ± 0.3 | 94.3 ± 0.6 |

Figure 4: Ablation of object-properties and object-relations from oracle. With only oracle object-category information, the oracle can’t learn these tasks in our sample budget.

Figure 5: Ablation of inter-object attention in policy. Without this, DQN cannot learn these tasks in our sample-budget. See §5.3 for details.

5.3 Ablations

Importance of object-properties & object-relations. To verify that capturing object-properties and -relations is key, we train an agent with only oracle object-category information. We find that this agent is not able to learn tasks that require using objects together as object-properties change in our sample-budget (see Figure 4).

Importance of inter-object attention. In order to verify the utility of using attention as an inductive bias for capturing object-relations, we ablate attention from both Attentive Object-DQN and our Attentive Object-Model. First, we look at two variants of Attentive Object-DQN without attention. The first is a regular DQN. In the second, we incorporate inter-object information by using the average of all present object-embeddings (DQN + Object Average). Neither learns our tasks in the sample-budget (see Figure 5).

Additionally, we look at performance where our policy can use inter-object attention but remove inter-object attention from our object-model. Without attention, we still get relatively good performance with 70% success rate; however, attention in the object-model helps increase this to 90%+ (see Figure 7 in our appendix for details).

6 Conclusion
We have shown that learning an attentive object-model can enable sample-efficient learning in high-fidelity, 3D, object-interaction domains without access to expert demonstrations or ground-truth object-information. Further, when compared to strong unsupervised learning baselines, we have shown that our object-model best captures object-categories, object-properties, and containment-relationships. We believe that LOAD is a promising steps towards agents that can efficiently learn complex object-interaction tasks.

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A Agent Details

A.1 Architectures and objective functions

We present the details of the architecture used for all models in table 3. All models shared the Attentive Object-DQN as their base. We built the Attentive Object-DQN using the rlkit open-source reinforcement-learning library.

**Attentive Object-DQN.** This is our base architecture. Aside from the details in the main text, we note that \( f^e \) is the concatenation of one function which encodes image information and another that encodes location information: \( f^e = f^e_{loc}(s^e) = f^e(s^e, s^{loc}) = [f^e_{loc}(s^e), f^e_{enc}(s^{loc})] \).

**Attentive Object-DQN + COBRA Object-Model:** each agent predicts the latent factors that have generated each individual object-image-patch. This requires an additional reconstruction network for the object-encoder, \( f_{recon}(z^{o,i}_t) \), which produces an object-image-patch back from an encoding and a prediction network \( f_{cobra} \) that produces the object-encoding for \( z^{o,i}_t \) at the next time-step. The objective function is:

\[
L_{recon} = E_{s_t} \left[ \sum_{l \in v_{t,i}} ||f_{recon}(z^{o,i}_t) - o_{t,i}||^2 \right] - E_{s_t} \left[ \sum_{l \in v_{t,i}} \beta \text{KL}(p(z^{o,i}_t | o_{t,i} || p(z^{o,i}_{t+1})) \right]
\]

(10)

\[
L_{pred} = E_{s_t} \left[ \sum_{l \in v_{t,i}} ||f_{recon}(f_{cobra}(z^{o,i}_t)) - o_{t+1,i}||^2 \right]
\]

(11)

\[
L_{cobra} = L_{recon} + L_{pred} - E_{s_t} \left[ \sum_{l \in v_{t,i}} \beta \text{KL}(p(z^{o,i}_t | o_{t,i} || p(z^{o,i}_{t+1})) \right]
\]

(12)

where KL is the Kullback-Leibler Divergence and \( p(z^{o,i}_t | o_{t,i}) \) is an isotropic, unit gaussian. We also model \( p(z^{o,i}_t | o_{t,i}) \) as a gaussian. We augment the Attentive Object-DQN so that \( z^{o,i}_t \) is the mean of the gaussian and so that a standard deviation is also computed. Please see Higgins et al. [2017] for more.

**Attentive Object-DQN + OCN:** the agent tries to learn encodings of object-image-patches such that patches across time-steps corresponding to the same object are grouped nearby in latent space, and patches corresponding to different objects are pushed apart. This also relied on contrastive learning, except that it uses it on image-pairs across time-steps. Following Pirk et al. [2019], the anchor is defined as the object-encoding \( z^{o,i}_t = f(o_{t,i}) \), which we will refer to as \( f \).

The positive is defined as the object-image-patch encoding at the next time-step with lowest \( L2 \) distance in latent space, \( f^+ = \arg\min_{z^{o,i}_{t+1}} ||z^{o,i}_t - z^{o,i}_{t+1}||^2 \). We then set negatives \{ \( f^- \) \} as the object-image-patches that did not correspond to the match. We note that augmenting Pirk et al. [2019] so that their objective function had temperature \( \tau \) was required for good performance. For a unified perspective with our own objective function, we write their n-tuplet-loss with a softmax (see Sohn [2016] for more details on their equivalence). The objective function is:

\[
L_{ocn} = \mathbb{E} \left[ -\log \left( \frac{\exp(f^+ f^+/\tau)}{\exp(f^+ f^+/\tau) + \sum_k \exp(f^+ f^-_k/\tau)} \right) \right]
\]

(13)

**Attentive Object-DQN + Ground Truth Object Info:** the agent doesn’t have an auxiliary task and doesn’t encode object-images. Instead it encodes object-information. For each object, we replace object-image-patches with the following information available in Thor:

1. object-category. If the object is a toaster, this would be the index corresponding to toaster.
2. What object is this object inside of (e.g. if this object is a cup in the sink, this would correspond to the sink index).
3. What object is inside this object of (e.g. if this object is a sink with a cup in it, this would correspond to the cup index).

The following correspond to “object-relations”:

1. distance to object (in meters)
2. whether object is visible (boolean)
3. whether object is toggled (boolean)
4. whether object is broken (boolean)
5. whether object is filledWithLiquid (boolean)
6. whether object is dirty (boolean)
7. whether object is cooked (boolean)
8. whether object is sliced (boolean)
9. whether object is open (boolean)
10. whether object is pickedUp (boolean)
11. object temperature (cold, room-temperature, hot)

A.2 Hyperparameter Search

**Attentive Object-DQN.** All models are based on the same Attentive Object-DQN agent and thus use the same hyperparameters. We searched over these parameters using “Attentive Object-DQN + Ground-Truth Object-Information”. We searched over tuples of the parameters in the “DQN” portion of table 4. In addition to searching over those parameters, we searched over “depths” and hidden layer size of the multi-layer perceptrons \( f_{loc}, Q_{loc}(o_{t}) \), and \( Q_{nav} \). For depths, we searched uniformly over \([0, 1, 2]\) and for hidden later sizes we searched uniformly over \([128, 256, 512]\). We searched over 12 tuples on the “Fill Cup with Water” task and 20 tuples on the “Place Apple on Plate & Both on Table” task. We found that task-performance was sensitive to hyperparameters and choose hyperparameters that achieved a 90% + success rate on both tasks. We fixed these settings and searched over the remaining values for each auxiliary task.

**Attentive Object-Model.** We experimented with the number of negative examples used for the contrastive loss and
### Networks

| Activation fn. (AF) |
|---------------------|
| $f_{\text{ego}}$   |
| $f_{\text{enc}}$   |
| $f_{\text{loc}}$   |
| $Q_{\text{int}}(o_i)$ |
| $Q_{\text{nav}}$   |
| $A(z_{\kappa}, Z_o)$ : $W_{h}^{1, 1}, W_{b}^{1}$ |
| $A(z_{\kappa}, Z_o)$ : $W_{h}^{2}, W_{2}$ |

| Parameters |
|------------|
| Attentive Object-DQN |
| Leaky ReLU (LR) |
| Conv(32-8-4)-AF-Conv(64-4-2)-AF-Conv(64-3-1)-AF-MLP(9216-512)-AF |
| Conv(32-4-2)-AF-Conv(64-4-2)-AF-Conv(64-4-2)-AF-MLP(9096-512)-AF |
| MLP(6-256)-AF-MLP(256-256)-AF |
| MLP(1280-256)-AF-MLP(256-256)-AF-MLP(256-8) |
| MLP(768-256)-AF-MLP(256-256)-AF-MLP(256-8) |
| MLP(512-64), MLP(512-64) |
| MLP(768-64), MLP(512-64) |
| Object-centric model |
| $f_{\text{model}}$ |
| $z_{a}: W^{o}, W^{b}$ |
| Scene-centric model |
| $f_{\text{model}}$ |
| $z_{a}: W^{o}, W^{b}$ |
| VAE |
| $f_{\text{recon}}$ |
| MLP(4096-512)-AF-Conv(64-4-2)-AF-Conv(64-4-2)-AF-Conv(32-3-2) |

| Table 3: Architectures used across all experiments. |

| Hyperparameter | Final Value | Values Considered |
|----------------|-------------|-------------------|
| Max gradient norm | 0.076 | log-uniform($10^{-4}, 10^{-1}$) |

| DQN |
| Learning rate $\eta_1$ | $1.8 \times 10^{-5}$ | log-uniform($10^{-6}, 10^{-2}$) |
| Target Smoothing Coefficient $\eta_2$ | 0.00067 | log-uniform($10^{-6}, 10^{-3}$) |
| Discount $\gamma$ | 0.99 | |
| Training $\epsilon$ annealing | $[1, 1]$ | |
| Evaluation $\epsilon$ | .1 | |
| Regular Replay Buffer Size | 150000 | |
| SIL Replay Buffer Size | 50000 | |
| Regular:SIL Replay Ratio | 7 : 1 | |
| Batchsize | 50 | |

| Attentive Object-Model |
| upper-bound $m$ | 85 | - |
| Number of Negative Examples | 20 | - |
| temperature $\tau$ | $8.75 \times 10^{-5}$ | log-uniform($10^{-6}, 10^{-3}$) |
| Loss Coefficient $\beta_{\text{model}}$ | $10^{-3}$ | - |

| Cobra Object-Model |
| KL Coefficient $\beta_{\text{kl}}$ | 26 | log-uniform($10^{-1}, 10^{2}$) |
| Loss Coefficient $\beta_{\text{cobra}}$ | 0.0032 | log-uniform($10^{-4}, 1$) |

| OCN |
| temperature $\tau$ | $5 \times 10^{-5}$ | log-uniform($10^{-6}, 10^{-3}$) |
| Loss Coefficient $\beta_{\text{ocn}}$ | 0.0047 | log-uniform($10^{-4}, 10^{-2}$) |

| Table 4: Hyperparameters shared across all experiments. |
found no change in performance. We performed a search over 4 tuples from the values in Table 4. We chose the loss-coefficient as the coefficient which put the object-centric model loss at the same order of magnitude as the DQN loss.

**COBRA Object-Model, OCN.** For each auxiliary task, we performed a search over 6 tuples from the values in Table 4. For each loss, we chose loss coefficients that scaled the loss so they were between an order of magnitude above and below the DQN loss.

**B Thor Implementation Details**

**B.1 Thor Settings**

**Environment.** While AI2Thor has multiple maps to choose from, we chose “Floorplan 24”. To reduce the action-space, we restricted the number of object-types an agent could interact with so that there were 10 distractor types beyond task relevant object-types. We defined task-relevant object-types as objects needed to complete the task or objects they were on/inside. For example, in “Place Apple on Plate & Both on Table”, since the plate is on a counter, counters are task object-types. We provide a list of the object-types present in each task with the task descriptions below.

**Observation.** Each agent observes an 84 × 84 grayscale image of the environment, downsampled from a 300 × 300 RGB image. They can detect up to 20 objects per-time-step within its line of sight, if they exceed 50 pixels in area, regardless of distance. Each object in the original 300 × 300 scene image is cropped and resized to a 32 × 32 grayscale image. Each agent observes its (x, y, z) location, and its pitch, yaw, and roll body rotation (φ1, φ2, φ3) in a global coordinate frame.

**Episodes.** The episode terminates either after 500 steps or when a task is complete. The agent’s spawning location is randomly sampled from the 81 grid positions facing North with a body angle (0°, 0°, 0°). Each agent receives reward 1 if a task is completed successfully and a time-step penalty of −0.04.

| Setting                      | Values          |
|------------------------------|-----------------|
| Observation Size             | 300 × 300       |
| Downsampling Observation Size| 84 × 84         |
| Object Image Size            | 32 × 32         |
| Min Bounding Box Proportion  | 50              |
| Max Interaction Distance     | 1.5m            |

Table 5: Settings used in Thor across experiments.

**B.2 Task Details**

For each task, we describe which challenges were present, what object types were interactable, and the total Key Semantic Actions available. We chose objects that were evenly spaced around the environment. The challenges were:

- **Challenge A:** the need for view-invariance (e.g. recognizing a knife across angles).
- **Challenge B:** the need to reason over ≥ 3 objects.
- **Challenge C:** the need to recognize and use *combined* objects (e.g. filling a cup with water in the sink or toasting bread in a toaster).

**Slice Bread.**

**Challenges:**

A: recognizing the knife across angles.

**Interactable Object Types:** 15

- CounterTop: 3, DiningTable: 1, Microwave: 1, Plate: 1, CoffeeMachine: 1, Bread: 1, Fridge: 1, Egg: 1, Cup: 1, Pot: 1, Pan: 1, Tomato: 1, Knife: 1

**Key Semantic Actions:**

1. Go to Knife
2. Pickup Knife
3. Go to Bread
4. Slice Bread

**Slice Lettuce and Tomato.** (order doesn’t matter)

**Challenges:**

A: recognizing the knife across angles.

**Interactable Object Types:** 17

- CounterTop: 3, DiningTable: 1, Microwave: 1, Plate: 1, CoffeeMachine: 1, Bread: 1, Fridge: 1, Spatula: 1, Egg: 1, Cup: 1, Pot: 1, Pan: 1, Tomato: 1, Lettuce: 1, Knife: 1

**Key Semantic Actions:**

1. Go to Knife
2. Pickup Knife
3. Go to Table
4. Slice Lettuce
5. Slice Tomato

**Slice Lettuce and Apple, and Potato.** (order doesn’t matter)

**Challenges:**

A: recognizing the knife across angles.

**Interactable Object Types:** 18

- CounterTop: 3, DiningTable: 1, Microwave: 1, Plate: 1, CoffeeMachine: 1, Bread: 1, Fridge: 1, Potato: 1, Egg: 1, Cup: 1, Pot: 1, Pan: 1, Tomato: 1, Lettuce: 1, Apple: 1, Knife: 1

**Key Semantic Actions:**

1. Go to Knife
2. Pickup Knife
3. Go to Table

For “Slice” tasks and “Make Tomato & Lettuce Salad”, we used an object image size of 64 × 64 to facilitate recognition of smaller objects. We decreased the replay buffer to have 90000 samples and the SIL replay buffer to have 30000 samples.
4. Slice Lettuce
5. Slice Apple
6. Slice Potato

**Cook Potato on Stove.**

**Challenges:**
A: recognizing the stove across angles.
B: needs to differentiate 3 objects: the stove knob, pot, and potato.
C: recognizing the potato in the pot.

**Interactable Object Types:** 21
1. StoveBurner: 4, StoveKnob: 4, DiningTable: 1, Microwave: 1, Plate: 1, CoffeeMachine: 1, Bread: 1, Fridge: 1, Potato: 1, Egg: 1, Cup: 1, Pot: 1, Pan: 1, Tomato: 1, Knife: 1

**Key Semantic Actions:**
1. Go to Potato
2. Pickup Potato
3. Go to Stove
4. Put Potato in Pot
5. Turn on Stove Knob

**Fill Cup with Water.**

**Challenges:**
A: recognizing the cup across angles and backgrounds.
B: recognizing the cup in the sink.
C: the need to recognize and use combined objects (e.g. filling a cup with water in the sink or toasting bread in a toaster).

**Interactable Object Types:** 18
- CounterTop: 3, Faucet: 2, Sink: 1, DiningTable: 1, Microwave: 1, CoffeeMachine: 1, Bread: 1, Fridge: 1, Egg: 1, Cup: 1, SinkBasin: 1, Pot: 1, Pan: 1, Tomato: 1, Knife: 1

**Key Semantic Actions:**
1. Go to Cup
2. Pickup Cup
3. Go to Sink
4. Put Cup in Sink
5. Fill Cup

**Toast Bread Slice.**

**Challenges:**
A: recognizing the toaster across angles.
C: recognizing the bread slice in the toaster.

**Interactable Object Types:** 21
- BreadSliced: 5, CounterTop: 3, Bread: 2, DiningTable: 1, Microwave: 1, CoffeeMachine: 1, Fridge: 1, Egg: 1, Cup: 1, Pot: 1, Pan: 1, Tomato: 1, Knife: 1, Toaster: 1

**Key Semantic Actions:**
1. Go to Bread Slice
2. Pickup Bread Slice
3. Go to Toaster
4. Put Breadslice in Toaster
5. Turn on Toaster

**Place Apple on Plate & Both on table.**

**Challenges:**
B: needs to differentiate 3 objects: the apple, plate, and table.
C: recognizing the apple on the plate.

**Interactable Object Types:** 16
- CounterTop: 3, DiningTable: 1, Microwave: 1, Plate: 1, CoffeeMachine: 1, Bread: 1, Fridge: 1, Spatula: 1, Egg: 1, Cup: 1, Pot: 1, Pan: 1, Apple: 1, Knife: 1

**Key Semantic Actions:**
1. Go to Apple
2. Pickup Apple
3. Put Apple on Plate
4. Pickup Plate
5. Go to Table
6. Put Plate on Table

**Make Tomato & Lettuce Salad.**

**Challenges:**
B: needs to differentiate 3 objects: the tomato slice, lettuce slice, and plate.
C: recognizing the tomato slice or lettuce slice on the plate.

**Interactable Object Types:** 32
- TomatoSliced: 7, LettuceSliced: 7, CounterTop: 3, Bread: 2, DiningTable: 1, Microwave: 1, Plate: 1, CoffeeMachine: 1, Fridge: 1, Spatula: 1, Egg: 1, Cup: 1, Pot: 1, Pan: 1, Tomato: 1, Lettuce: 1, Knife: 1

**Key Semantic Actions:**
1. Go to table
2. Pickup tomato or lettuce slice
3. Put slice on Plate
4. Pickup other slice
5. Put slice on Plate

**B.3 Interaction Dataset**

In order to measure and analyze the quality of the object representations learned via each auxiliary task, we created a dataset with programmatically generated object-interactions and with random object-interactions. This enabled us to have a diverse range of object-interactions and ensured the dataset had many object-states present.

**Programatically Generated object-interactions.** This dataset contains programmatically generated sequences of interactions for various tasks. The tasks currently supported by the dataset include: pickup X, turn on X, open X, fill X with Y, place X in Y, slice X with Y, Cook X in Y on Z. For each abstract task type, we first enumerate all possible manifestations based on the action and object properties. For example, manifestations of open X include all objects that are openable. We exhaustively test each manifestation and identify the ones that are possible under the physics of the environment. We explicitly build the action sequence required to complete each task. Because we only want to collect object-interactions, we use the high level “TeleportFull” command for navigation to task objects. The TeleportFull command allows each agent to conveniently navigate to desired task objects at a particular
location and viewing angle. For example, the sequence for place X in Y is: TeleportFull to X, Pickup X, TeleportFull to Y, and Put X in Y. An agent will execute each action until termination. We collect both successful and unsuccessful task sequences. There is a total of 156 unique tasks in the dataset and 1196 individual task sequences amounting to 2353 (state, action, next state) tuples.

**Random object-interactions.** The random interaction dataset consists of (state, action, next state) tuples of random interactions with the environment. An agent equipped with a random action policy interacts with the environment for episodes of 500 steps until it collects a total of 4000 interaction samples.

**Features in dataset.** We study the following features: Category is a multi-class label indicating an object’s category. The following are binary labels. Object-properties contains 6 features such as whether objects are closed, turned on, etc. Containment Relationship contains 2 features: whether an object is inside another object or whether another object inside of it. For each feature-set, we present the mean average precision and standard error for each method across all 8 tasks in Table 2.

**Training.** We divided the data into an 80/20 training/evaluation split and trained for 2000 epochs. We reported the test data results.

### C Additional Results

#### C.1 Success rate of competing auxiliary tasks

To supplement the training success curves in §5.1, we also provide the maximum success rates obtained by each auxiliary task in Table 6. In Table 6, we find that using Ground-Truth Object-Information is able to get the highest success rate on 7/8 tasks. It only achieves 80% on “Slice Apple, Potato, Lettuce”, a task that requires using 4 objects, which is consistent with our finding that tasks that require more objects have a higher sample-complexity.

In terms of maximum success rate, looking at Table 6, our Attentive Object-Model comes closest to Ground-Truth Object-Information on 5/8 tasks and is tied on 3/8 tasks with the COBRA Object-Model. However, for tasks that require using objects together, such as “Fill Cup with Water” where a cup must be used in a sink or “Toast Bread Slice” where bread must be cooked in a toaster, the COBRA Object-Model exhibits a higher sample-complexity.

#### C.2 Ablating inter-object attention from Attentive Object-Model

We ablate inter-object attention from our agent’s model. In Figure 7, we find that the agent can perform reasonably well without incorporating attention into the object-model, achieving a success rate of about 70%. With attention however, the agent can get above a 90% success rate.
| Auxiliary Task | Slice Bread | Slice Lettuce and Tomato | Slice Apple, Potato, Lettuce | Cook Potato on Stove | Fill Cup with Water | Toast Bread Slice | Apple on Plate, Both on Table | Make Salad |
|----------------|-------------|--------------------------|-------------------------------|---------------------|-------------------|-------------------|------------------------------|-----------|
| No Auxiliary Task | 80.6 ± 7.8  | 89.6 ± 3.0               | 23.5 ± 14.7                   | 80.6 ± 12.9        | 96.3 ± 0.7       | 48.5 ± 18.2       | 20.2 ± 16.1                 | 81.4 ± 7.3 |
| Object Contrastive Network (OCN) | 77.6 ± 13.9 | 72.0 ± 15.1               | 43.4 ± 16.3                   | 70.9 ± 9.6         | 38.2 ± 20.9      | 3.0 ± 1.9          | 23.2 ± 18.0                 | 90.2 ± 1.8 |
| COBRA Object-Model | 95.3 ± 1.2  | 93.4 ± 1.4               | 71.7 ± 16.2                   | 88.6 ± 3.3         | 35.0 ± 19.3      | 15.1 ± 13.5       | 74.1 ± 14.8                 | 92.7 ± 1.4 |
| Attentive Object-Model | 94.4 ± 1.8  | 94.2 ± 0.5               | 81.9 ± 4.4                    | 91.7 ± 2.3         | 94.5 ± 1.0       | 91.1 ± 2.1         | 88.1 ± 3.4                  | 92.8 ± 0.5 |
| Ground-Truth Object-Info | 98.6 ± 0.2  | 98.8 ± 0.2               | 80.2 ± 10.8                   | 97.7 ± 0.2         | 95.2 ± 0.4       | 93.3 ± 2.3         | 90.5 ± 3.2                  | 96.6 ± 0.2 |

Table 6: Maximum success rate achieved by competing auxiliary tasks during training.

Figure 6: **Top-panel**: we present the success rate over learning for competing auxiliary tasks. We seek a method that best enables our Attentive Object-DQN (grey) to obtain the sample-efficiency it would from adding Ground-Truth Object-Information (black). We visually see that LOAD (red) is best able to learn more quickly on tasks that require using containment-relationships (e.g. a cup in a sink) or recognizing changing object properties (e.g. a toaster turning on with bread in it).

**Bottom-panel**: by measuring the % AUC achieved by each agent w.r.t. to the agent with ground-truth information, we can measure how close each method is to the performance of an agent with ground-truth object-knowledge. We find LOAD (red), which learns an attentive object-model best closes the performance gap on 6/8. We hypothesize that this is due to our object-model’s ability to capture oracle object-information about object-categories, object-properties, and object-relations. We show evidence for this in Table 2.
Figure 7: Ablation of inter-object attention in object-model. We show that incorporating inter-object attention into our object-model leads to better performance.