Egocentric scene context for human-centric environment understanding from video

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Abstract. First-person video highlights a camera-wearer’s activities in the context of their persistent environment. However, current video understanding approaches reason over visual features from short video clips that are detached from the underlying physical space and only capture what is directly seen. We present an approach that links egocentric video and camera pose over time by learning representations that are predictive of the camera-wearer’s (potentially unseen) local surroundings to facilitate human-centric environment understanding. We train such models using videos from agents in simulated 3D environments where the environment is fully observable, and test them on real-world videos of house tours from unseen environments. We show that by grounding videos in their physical environment, our models surpass traditional scene classification models at predicting which room a camera-wearer is in (where frame-level information is insufficient), and can leverage this grounding to localize video moments corresponding to environment-centric queries, outperforming prior methods. Project page: http://vision.cs.utexas.edu/projects/ego-scene-context/

1 Introduction

Egocentric video offers a unique view into human activities through the eyes of a camera-wearer. Understanding this type of video is core to building augmented reality (AR) applications that can assist humans by answering their questions, recalling events, or anticipating their needs based on their activity. Ego-video is the subject of several recent datasets and benchmarks that are driving new research [46, 68, 13, 27].

A key feature of the egocentric setting is the tight coupling of the camera-wearer and their environment as they repeatedly traverse a persistent physical space, potentially over multiple hours (or days). This raises an important need for human-centric environment understanding — to learn representations from video that capture the camera-wearer’s activities in the context of their environment. Such representations are important to answer questions like “what room is the camera-wearer in right now?”, or “when was the camera-wearer last near the sink?”. The former requires reasoning across video frames spread in time to build a coherent picture of the scene. The latter requires reasoning about the
Fig. 1: Main idea. Left: Existing video understanding methods rely largely on aggregating what is seen in short video clips over time (e.g., TV is seen as the person walks up to it). Right: We propose to ground video in its underlying 3D environment and learn human-centric environment representations that are predictive of their surroundings. Such representations should (1) relate observed frames based on their physical location — the same TV from earlier in the video (blue box, viewed from ✗); plant to the right (green box, viewed from ✗) — and (2) encode features for potentially unseen surrounding content (yellow boxes: couch behind the TV, lamp to the left). Blue arrows show direction of content captured in each view vs. person’s current position.

camera-wearer’s location relative to other objects, regardless of their visibility (e.g., a person may be at the sink, but looking at the mirror above it).

Despite its importance, there has been only limited work on learning human-centric environment representations. Current video understanding approaches segment a video into short-clips (1-2s long) and then aggregate clip features using additional modules (e.g., recurrent, graph or transformer-based networks) for tasks like action forecasting [24, 27, 53, 26], temporal action localization [86, 48, 49, 87], episodic memory [27, 15], and movie understanding [83]. Critically, the clip features encode only what is immediately visible in a short time window. Aggregating clip features over time is therefore insufficient to capture the spatial relationships between the camera-wearer and the environment (as needed to answer, e.g., where is the camera-wearer physically located? what objects are within reach?). Alternatively, approaches that use explicit pose information (e.g., from SLAM) are either limited to reasoning about camera-wearer locomotion for short-term forecasting [55, 63, 29] or use pose as a means to learn global, environment-level affordances by propagating labels over space [62] or topological graph structures [53] — they do not learn representations that link the camera-wearer’s observations at a particular time to their underlying environment.

To address these shortcomings, we propose environment-aware video representations that encode the surrounding physical space. Specifically, we define the local environment state at each time-step of an egocentric video as the set of objects in front, to the left, right, and behind the camera-wearer. First, we use this state as supervision to train a transformer-based video encoder model that aggregates visual (RGB) and odometry (pose) information across a video to build an environment memory; then we query it to predict the local state at any point in the video. To do well, the model must link visual observations based on their pose to reason about the collective environment. Moreover, it
cannot merely maintain a record of objects seen — it must encode features that are predictive of the local state, which requires anticipating the camera-wearer’s (potentially unseen) surroundings. See Fig. 1. Once trained, given an observation and its pose from a new video, our model produces an auxiliary “environment feature” to complement existing video clip features.

An important practical question is how to supervise such a representation. Sourcing local state labels requires agent and object positions and omnidirectional visibility at each time step. This is challenging as egocentric videos only offer sparse coverage of the environment. Furthermore, they are prone to object detection, tracking, and SLAM failures due to characteristic head motions and blur. Therefore, for training we turn to videos generated by agents in simulation. This allows us to sample diverse, large-scale trajectories to cover the environment, while also providing ground-truth local state. Once trained with simulated video, we apply our models to real-world videos from new, unseen environments.

We demonstrate our approach on two key tasks — room prediction: inferring the room category that the camera wearer is physically in as they move through their environment, and episodic memory retrieval: localizing the answer to a natural language query in an egocentric video. These tasks can support many potential applications, including AR systems that can reason about both the user and the environment to offer relevant assistance. For example, an AR assistant could identify the rooms visited by the camera-wearer to give location-specific suggestions for chores to complete; or recall the last time the camera-wearer was near the sink, to check if the tap was left turned-on.

Our experiments show how we leverage video walkthroughs from simulated agents in the Gibson dataset [84] to learn human-centric environment models, which ultimately enable room prediction and episodic memory retrieval downstream on both simulated videos from Matterport3D [7] and real-world videos from the HouseTours dataset [8]. Our results show that our local state pre-training strategy outperforms both naive methods to associate pose information with video frames as well as existing models for structured video understanding, leading to improved performance over current scene classification and episodic memory retrieval models.

In summary, we make the following contributions:

- We present a framework to learn environment-aware representations from videos by capitalizing on both geometric (relative object location) and semantic (object class) cues in our proposed “local environment state” task.
- We are the first to demonstrate the value of 3D simulation data for human-centric environment understanding in real-world videos, and we propose strategies to address the sim-to-real domain gap.
- We show that models equipped with our learned environment features outperform traditional scene classifiers [88] at predicting which room a camera-wearer is in, and can localize the answer to environment-centric queries in videos better than current moment retrieval methods [86].
2 Related work

Video understanding in 3D environments. Prior work encodes short video clips [5, 78, 57, 35], or temporally aggregates them to incorporate additional context [82, 24, 86, 48, 49, 87, 83]. However, these methods treat the video as a temporal sequence and fail to capture the spatial context from the underlying persistent environment. For egocentric video, prior work has used structure from motion (SfM) to map people and objects for trajectory [55] and activity forecasting [29] and action grounding in 3D [62, 14]. These approaches localize the camera-wearer but do not learn representations for the camera-wearer’s (potentially unobserved) surroundings. The model of [50] associates features to voxel maps to localize actions; however, they require a pre-computed 3D scan of the environment at training and inference. Ego-topo [53] builds topological graphs of the environment from egocentric video; however, they offer weak pose information (rough spatial connectivity) and generate representations to summarize the entire video (by simply averaging node features) rather than for a specific time point. In contrast, we go one step further and explicitly learn environment features for each step of an egocentric video using our local state task.

Video representation learning. Traditional video understanding methods learn representations by training models on large, manually curated video datasets, typically labeled for action recognition [5, 51, 28]. Recent self-supervised learning (SSL) approaches eliminate the supervision requirement by leveraging implicit temporal signals [81, 52, 54, 39, 33, 77, 79, 80, 61] or by adapting image SSL techniques for video [23]. In contrast, we learn features that encode the local spatial-state of the environment (as opposed to temporal signals). Further, we show how to leverage state information that is readily accessible in simulation, but not in video datasets (i.e., locations and semantic classes of objects surrounding the agent) for training.

Environment features for embodied AI. In embodied AI, pose-estimates are used to build maps [11, 9, 58], as edge features in graphs [10, 8], as spatial embeddings for episodic memories [22], or to project features to a grid map [30, 37, 6]. However, these approaches are explored solely in simulation; they typically require accurate pose-estimates or smooth action spaces to build spatial representations, and are not directly applicable to egocentric videos. Our idea is also related to research on world-models for predicting future agent states [20, 31, 32] and methods for reconstructing unseen panoramic viewpoints [40, 69, 43] that hallucinate the effect of agent actions to aid decision-making. While our approach is similarly motivated, we instead aim to learn features that capture the local-state immediately around an egocentric camera-wearer for better real-world video understanding. EPC [59] proposes a self-supervised “masked-zone prediction” task to learn environment-level features that capture high-level geometry and semantics suitable for visual navigation. In contrast, we learn environment-aware features that capture local agent-state (e.g., what objects are near me?) more suited to video understanding. We compare these in our experiments.

Learning from simulated data. Prior work has proposed cost-effective ways to generate large-scale synthetic image datasets for various vision tasks [71,
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73, 17, 38, 21, 64]. In robotics, simulation environments have been developed to quickly and safely train policies, with the eventual goal of transferring them to real world applications [42, 74, 44, 7, 84, 66, 60, 72]. The resulting sim-to-real problem, where models must adapt to changes between simulator and real-world domains, is an active area of research [73, 41, 65, 4, 1]. Simulated data for video understanding is much less explored. Prior work has synthesized data for human body pose estimation [12, 75, 85, 19], trajectory forecasting [47] and action recognition [70]. Rather than model human behavior, our approach aims to capture the semantics of the environment surrounding the camera-wearer.

3 Approach

Our goal is to generate features that encode the local surroundings of the camera-wearer — where they are and what objects are nearby (even if not currently visible) — to equip egocentric video models with the ability to reason about the underlying environment.

A naive way to do this is to localize the camera-wearer in the environment, and associate the resulting camera pose with each frame of the video before encoding; however, training the model to effectively utilize pose is non-trivial since location alone does not reveal where other objects are relative to the camera-wearer. Detecting and tracking objects over time along with camera localization can help bridge this gap, but is limited to objects clearly visible in the video, and cannot anticipate unseen surroundings.

Instead, we introduce an approach that leverages simulated environments where perfect state information is available to train models that aggregate visual and pose information over time. To this end, we first define the local state prediction task in simulation (Sec. 3.1). Next, we introduce our transformer-based encoder-decoder architecture that predicts the local state at a given time in the video (Sec. 3.2). Finally, we show how to leverage our model trained in simulation to generate environment features corresponding to frames in real-world egocentric videos (Sec. 3.3).

3.1 Local environment state

We require a model that is aware of not just what is immediately visible in a single frame, but also of the camera-wearer’s surroundings. We therefore define the local environment state of the camera-wearer as the relative direction of each object class — i.e., is the object to the front, left, right, behind or not visible in any direction around the camera-wearer — and train a model to predict this state. Our definition of local state takes inspiration from cognitive science [34, 45], and offers supervision signals that are both geometric (where are objects with respect to the camera-wearer) and semantic (semantic object labels), which we observe leads to strong representations. We study other variants in Sec. 4.

More formally, let $\mathcal{O}$ be a set of object classes. For a frame $f$ from a video walkthrough in an environment the local state $y$ is a $|\mathcal{O}|$-dimensional vector which represents the relative direction of instances of each object class that are
Fig. 2: **Local environment state illustration.** Models must classify the direction of each object class relative to a particular query frame in a video. Views in each direction and their corresponding objects are shown for clarity (left panel), but the video only contains the forward view (top left) at each step. Note that not all parts of the environment are seen during a walkthrough (white vs. grey regions) — models must both link observations based on their shared space, as well as anticipate their unseen surroundings to solve this task. Best viewed in color.

Near the camera-wearer. If the camera-wearer is at position \( p_a \) in the environment, \( y \) is calculated using the position \( p_i \) of the nearest instance of each object class \( o_i \in O \) as follows\(^4\)

\[
y = \begin{cases} 
\theta(p_a, p_i) & \text{if } d(p_a, p_i) < \delta \\
0 & \text{otherwise}
\end{cases}
\]

where \( d(p_a, p_i) \) is the Euclidean distance between the camera-wearer and object \( o_i \), \( \delta \) is a distance threshold for nearby objects (we set \( \delta = 3.0 \) meters, beyond which visible objects are small), and \( \theta(p_a, p_i) \in [1..4] \) calculates the relative angle of the object with respect to the agent’s current heading and discretizes it into four cardinal directions – forward, right, behind, left. Labels for objects that are too far away or cannot be seen from any angle from the agent’s current position are set to zero. See Fig. 2.

We then train a model to predict the local state given a video frame. Once trained, such a model can relate what is immediately visible in a frame with the possibly hidden surroundings of the camera-wearer and produce features that are environment-aware.

However, obtaining camera-wearer pose and every object’s location to construct our labels is non-trivial for egocentric videos where trajectories have limited environment coverage, and where camera localization and tracking is error prone. We address these issues in the next section by leveraging videos in simulated environments for training.

### 3.2 Environment-aware pretraining in simulation

As discussed above, to source local state labels, we generate a dataset of video walkthroughs of agents in a variety of simulated 3D environments for which

\(^4\) We consider the nearest instance (vs. all instances) as it allows us to cast the prediction task as a discriminative classification problem, rather than for example, a regression task.
agent and object poses are accessible at all times (details in Sec. 4.1). We train an encoder model to embed visual and pose information over time into an environment memory. Then, we train a decoder model that uses this memory to infer the local state corresponding to any given query frame. We implement this model as a transformer encoder-decoder model. Our architecture builds on prior work [22, 59] though our main idea to pre-train representations using the local state is potentially compatible with other architectures.

Specifically, for a video walkthrough $V$ with associated RGB frames $\{f_t\}_{t=1}^T$ and camera poses $\{p_t\}_{t=1}^T$, and a given query frame and pose $(f_q, p_q)$ — we predict the local state $y_q$ as follows. First, each frame is encoded jointly with pose to generate the observation representation using a linear transform $M_p$.

$$x_t = M_p([f_t; \Delta p_t]), \quad (2)$$

where $\Delta p_t$ is the relative pose between the frame’s pose $p_t$ and the query frame’s pose $p_q$.\(^5\) Next, we sample $K$ video frames to construct an environment memory using a transformer encoder $E$, which updates input frame representations using self-attention.

$$\{e_1, ..., e_K\} = E(x_1, ..., x_K). \quad (3)$$

The resulting memory represents features for each time-step that contain propagated information from all other time-steps. Compared to prior work [24, 86, 48, 49, 87], our encoder has the ability to relate observations based on not just visual characteristics and their temporal ordering, but also their relative spatial layout in the environment, which we show is important for predicting local state. A transformer decoder $D$ then uses the query image feature $f_q$ to attend over the encoded memory to produce the output representation $h_q$,

$$h_q = D(\{e_1, ..., e_K\}, f_q), \quad (4)$$

which is finally used to predict the local state $\hat{y}_q = M_h([f_q; h_q])$, where $M_h$ is a linear classifier head. The network is trained to minimize cross-entropy between the predicted and the target state labels for each direction $\mathcal{L}_{ce}(\hat{y}_q, y_q)$.

See Fig. 3 (left) and Supp. for more architecture details. Learning this task involves aggregating information about frequently seen objects across time, as well as anticipating features for rare (or unseen) objects (23% of our training walkthroughs involve predicting objects that are rarely or never seen).

Once trained, given a video in a new environment and a target time-point of interest, our model constructs an environment memory, predicting the local state based on information aggregated through the entire test video. Note that the memory is query-specific and is computed separately for each query of interest. Importantly, the features $h_q$ contain valuable information about the immediate surroundings of the agent and can be used as an environment feature to complement traditional video features. For example, a video feature may encode a

\(^5\) Relative pose encodings reduce the model’s burden to aggregate pose over time to relate the query observation and have been used in prior embodied navigation models [22, 59]. Our experiments compare other pose encodings.
Fig. 3: Model framework. **Left panel:** Our model encodes video walkthroughs (in simulation) into an environment memory that is used to predict the local environment state for any given query frame (Sec. 3.2). **Right panel:** Once trained, our model builds and queries an environment memory for any time-point of interest in a real-world video, to generate an environment-feature for downstream video tasks performed in disjoint and novel scenes (Sec. 3.3). ⊕ = concatenation.

TV screen in a person’s view, but the environment feature would augment it to capture the couch they are sitting on or the lamp next to them, as it was trained to predict this local state information.

### 3.3 Environment-memory for video understanding

Next, we leverage our environment-memory model for real-world video tasks. A video understanding task defines a mapping from a sequence of video clips $V = \{c_1, ..., c_N\}$ to a task label. We consider two video tasks: (1) **Room prediction** where the model must classify which room $r_t$ the camera-wearer is in (e.g., living room, kitchen) at time $t$ in the video, and (2) **Episodic memory retrieval** where the model must identify the temporal window $(t_s, t_e)$ in the video that answers an environment-centric query $q$ specified in natural language. See Fig. 4.

Current models produce clip features that encode only what is immediately visible. While this is reasonable for short-horizon tasks like action recognition, it is insufficient for the tasks above that require reasoning about the agent’s location and surroundings. We therefore use our environment-memory model to enhance standard clip features of current models with context from the camera-wearer’s surroundings.

For this, we first compute the pose of the camera-wearer in the video using a structure from motion (SfM) framework (COLMAP [67]). This provides a mapping from frames in the video to their poses. Following Sec. 3.2, we uniformly sample $K$ frames from the input video to build our environment memory. We select the center frame $f_i$ of each input video clip in $c_i \in V$ as query frames and build a separate environment memory conditioned on each query frame’s pose using our environment encoder $\mathcal{E}$, following Equation 3. Finally, we use our environment decoder $\mathcal{D}$ along with each encoded memory to produce a set of output features, one per input clip

$$h_i = \mathcal{D}(\{e_1^i, ..., e_K^i\}, f_i).$$

(5)
Each environment feature then enhances the original clip feature as follows

$$g_i' = W^T_E [g_i; h_i] + b_E,$$

where $g_i$ is the original clip feature for clip $c_i$ and $W_E, b_E$ are linear transform parameters. See Fig. 3 (right).

The new clip features $\{g'_1, ..., g'_N\}$ consolidate features from what is directly visible in a short video clip and features of the (potentially unseen) space surrounding the camera-wearer. Put simply, our representation implicitly widens the field of view for tasks that reason about short video clips by providing a way to access features of their surroundings in a persistent, geometrically consistent manner. Our features can be used as a drop-in replacement in video understanding models, as we will show next.

4 Experiments

We evaluate how our environment features learned in simulation can benefit video understanding tasks in real-world video.

4.1 Simulator environments and video datasets

We use the Habitat simulator [66] with photo-realistic 3D Gibson [84] environments to generate simulated video walkthroughs. We use 88 scenes with semantic annotations [2] containing instances from the $|O| = 20$ most frequent object classes. We split these environments randomly into 71 training and 17 validation environments and generate \(50k\) walkthroughs, each 512 steps long, taken by a shortest-path agent that randomly samples goal locations in the environment and navigates towards them (move forward, turn right/left 30°). For each time-step, we obtain the ground-truth local state from the simulator required in Sec. 3.1. (i.e., camera pose, object labels and relative positions at each time-step). Though the walkthroughs involve discrete actions, they share characteristics with real-world video (cameras at head-level; views covering the environment) — making them valuable for transfer. See Supp. for further details.

We use two sources of egocentric video to test our models. (1) Matterport3D [7] contains simulated video walkthroughs from 90 photo-realistic 3D scenes. It offers novel scenes with distinct visual characteristics and novel object distributions compared to Gibson. With this, we test our model’s robustness to this domain shift, albeit in the controlled simulated video setting. We use the standard train/val/test split of 146 long video walkthroughs generated in prior work [6], each subdivided into smaller 512-step trajectories. (2) HouseTours [8] contains 119 hours of real-world video footage of house tours from YouTube. These videos are generated by people walking in houses and capture high quality images tied to human ego-motion. We keep video clips where the camera can be localized, amounting to \(~32\) hours of video from 886 houses, and we split randomly on houses for training, validation, and testing. Note that in contrast to the simulated videos used for pretraining, these videos are captured by humans in real-world houses. Like Matterport3D, the videos are captured in
Fig. 4: Scene understanding in third-person photos vs. human-centric environment understanding. Left panel: Well-framed, canonical images from Places365 used to train scene recognition models have quite different properties than much scene content observed in egocentric video. Center and right panel: Embodied video streams from Matterport3D and HouseTours. Here, it is valuable to model the underlying environment, rather than just what is visible in short clips. For example, the person does not explicitly look at the staircase while walking down it (center, row 2); the spatial relation between the person, the flowers and the staircase is important to answer the question (right, row 2).

a disjoint set of scenes that are not used during training. With this dataset, we test our model’s ability to generalize along two axes — to real-world visuals as well as new, unseen environments.

We collect labels for each video dataset corresponding to the tasks in Sec. 3.3. For Matterport3D, we source these labels directly from the simulator — room labels from 9 categories are accessible for the room prediction task, while episodic memory queries can be generated given object labels and locations. For HouseTours, we crowd-source ground truth room labels across 21 categories for room prediction as well as natural language queries for the episodic memory task. The types of queries are discussed in Sec. 4.7. See Supp. for data collection details and statistics and Fig. 4 for examples.

4.2 Bridging sim-to-real distribution shift

While the simulation-based pretraining in Sec. 3.2 and video understanding tasks in Sec. 3.3 both focus on indoor home scenes, several inconsistencies exist between them (the “sim-to-real gap”). First, the objects and rooms seen during pre-training do not necessarily match the real-world video. However, this is not problematic, as our goal is to learn how to aggregate observations and pose — the classification task (Sec. 3.1) is a means to learn representations that achieve this, and is not relevant downstream. Next, videos from discrete actions in simulation do not resemble fluid human motion. However our approach characterizes the environment from frames (not motion) for which sub-sampling video frames is sufficient. Finally, the ground truth pose in simulation is accurate and noise-free compared to the inferred pose in real video. We introduce noise into pose during pre-training and investigate its effect in our experiments. Finally, we use frozen ImageNet [16] pre-trained image encoders to reduce the impact of misaligned visuals when training on simulated video.
4.3 Experiment setup

For pre-training, we use 2048-dimension features extracted from an ImageNet pretrained ResNet50 [36] model to represent each video frame. Relative pose is encoded as a vector \((x, y, \theta)\). Our encoder \(E\) and decoder \(D\) are 2-layer transformers [76] with hidden dimension 128. \(K = 32\) frames are sampled from each video to populate the encoder memory. Our models are trained for 200 epochs. We select the model with the lowest validation loss to evaluate downstream.

For downstream tasks, we sample \(K = 32\) frames for our memory. For ROOM PREDICTION, we generate a single environment feature aligned with the query frame. For EPISODIC MEMORY we generate one feature per input clip. We fine-tune our pre-trained model. Full architecture and training details are in Supp.

4.4 Baselines

- **Vanilla** represents the status-quo video model that uses clip features for prediction. The architecture varies depending on the task. For ROOM PREDICTION we use a popular scene recognition model [88]. For EPISODIC MEMORY we use a state-of-the-art moments localization network 2D-TAN [86].
- **Obj features** trains an image encoder to classify objects in frames from our simulated walkthrough data, allowing it to benefit from the additional supervision and data available to our model.
- **Pose embed** directly concatenates pose embeddings to each input clip feature to test whether raw pose is valuable without additional pre-training.
- **Ego-topo [53]** concatenates features from a graph convolutional network operating on the video graph constructed following [53]. To enhance this model, we use available pose information to construct the graph (details in Supp).
- **EPC [59]** trains an environment memory model to predict masked zone features conditioned on pose, to capture global environment structure suitable for visual navigation. Like ours, this trains on simulated walkthrough data.
- **Ours** trains our environment memory model to predict the local state following Sec. 3.1, resulting in features that are predictive of the camera-wearer surroundings.

We also examine variants of our approach that use our architecture (Sec. 3.2) but leverage alternate pretraining strategies.

- **Scratch** does not benefit from pretraining — it randomly initializes parameters and trains directly on the video task. This represents typical transformer-based models for embodied navigation [22], but with an additional decoder.
- **SSL** trains our environment memory to predict masked frame features conditioned on time, similar to self-supervised approaches for language modeling (e.g., BERT [18]).
- **Pano feat** trains our environment memory to regress to image features in each direction, inspired by prior work on panorama completion [40, 69, 43].
- **Env state** predicts local state labels that encode both semantic and geometric information from object locations and classes. This is OURS above.
These baselines represent various strategies to incorporate environment information into input representations ranging from directly using camera-wearer pose (POSE EMBED), to using topological graph-based video representations (EGO-TOPO) to pose-based feature learning (EPC). The model variants test alternate pretraining objectives while keeping the architecture and training data fixed. In all cases, we encode RGB images using a frozen ImageNet pre-trained CNN. Note that by themselves, each method produces an environment feature, which is used to enhance the input clip features following Equation 6. The basic video task model used by all methods is the same — the VANILLA model — only the input to this model changes across methods.

4.5 Local state pretraining

We begin by evaluating our model’s ability to predict the direction of each object in its vicinity by calculating the average precision (AP) for each direction. Predicting objects forward, right and left achieve 33.8, 36.1 and 34.1 AP respectively. Predicting labels behind the camera-wearer is the hardest with 24.4 AP. We visualize the attention weights learned by our model to link relevant observations to the query in Fig. 5. Our model learns to select informative views for the local state prediction task. Importantly, these views are not simply temporally adjacent frames or views with high visual overlap — they are views that help reveal the surroundings of the selected query. For example, the view with highest attention score (0.82) looks at the dining table directly behind (left panel), allowing our model to benefit from information beyond its field of view.

4.6 Environment features for room prediction

We evaluate our method on predicting what room the camera-wearer is in at a particular time-step in a video. All models have access to the full video, though inference is at a single time-point.

Baseline. Our VANILLA model is a classifier trained on features from a Places365 [88] scene classification model. We use the authors’ pretrained model. Features are max-pooled across an $N = 8$ frame window around the time-step of interest for additional context before prediction, as a single frame may be uninformative.
Table 1: Room prediction top-1 accuracy. Our method outperforms baselines, especially for hard instances that require local environment reasoning. Scene classification prediction entropy is used to distinguish easy/hard instances (see Sec. 4.6). Results are averaged across three runs.

(e.g., facing a wall). We generate an environment feature aligned with the center of the window.

**Evaluation.** We report top-1 accuracy across all instances and split by difficulty. We sort Matterport3D instances by the prediction entropy of a pre-trained Places365 model trained on canonical scene images, and set a threshold to select 30% of them as “hard”, where frame-level information is insufficient for accurately predicting the room type.

Our results are in Table 1. All models perform better on HouseTours compared to Matterport3D since the house tours were captured explicitly to provide informative views of each room. Despite having access to all data, OBJ FEATURES does not benefit as it is trained to recognize far fewer objects than traditional ImageNet based encoders (20 vs. 1000 classes) resulting in weaker representations. Naively incorporating pose in POSE EMBED or using weak pose information in EGO-TOPO results in small improvements over the baseline. EPC is explicitly trained to use pose information to link observations, and outperforms most baselines. However, our approach performs the best across both datasets, especially on the hard instances where the surrounding environment-context is important to generate an accurate prediction (over just the visible clip-level context). Note that despite training our models entirely in simulation, and with videos from a set of disjoint environments, our models are able to produce features that are useful for downstream tasks on real-world videos.

Our experiments on model variants in Table 1 (right) show that even with access to pose in our transformer-based model, training from scratch or using self-supervised objectives offer limited benefits. However, alternate objectives that use supervision from the simulator have value. PANO FEAT predicts image features in cardinal directions — a form of our proposed local environment state — and performs reasonably well on easy instances, but falls short of ENV STATE on hard instances. Encoding both geometric and semantic information into the learned representation provides the best result.

### 4.7 Environment features for episodic memory retrieval

Next we evaluate our method on temporal localization of templated natural language queries in a video (e.g., “when did I last see obj X in room Y”, “when did I last visit obj X”). Broadly, we group these templates into “see” queries, where the object of interest is directly visible across frames, and “visit” queries,
Table 2: Episodic memory retrieval results. Our approach performs particularly well on “visit”-style queries that require reasoning about the camera-wearer’s position relative to their surroundings, rather than about what is immediately visible. Results avg across three runs.

where the camera-wearer navigates near the object or room, but may not actually see it, which is harder and requires additional reasoning about the agent’s pose and the environment-level context over the video frames. See Supp. for full list and Fig. 4 (right panel) for examples.

Baseline. We use an existing implementation of 2D-TAN [86] as the VANILLA model for our experiments. The model is provided with $N = 128$ clips sampled uniformly from the full video to generate predictions. We use average-pooled ResNet-50 features as clip features and generate an environment feature aligned with each input clip. Architecture details are in Supp.

Evaluation. We report Rank $n@m$ metrics commonly used in temporal moment localization literature [25, 86]. This metric measures the percentage of queries that are correctly retrieved within the top $n$ predictions. A predicted moment is correct if it overlaps sufficiently with the ground truth moment (IoU > $m$). For both datasets we report Rank 1@0.3, as the moments are typically short and higher threshold values result in very few matches. Results for other IoU thresholds are in Supp.

Our results are in Table 2. Similar to ROOM PREDICTION, instances in Matterport3D are harder as the agents in the videos follow shortest paths across the environment, and do not focus on particular objects while navigating. As a result, moments are quick transitions between objects and locations, and contain only short glimpses of them. OBJ FEATURES suffers the same limitations discussed in Sec. 4.6, namely weaker representations compared to ImageNet pretrained models. POSE EMBED has varying success at linking nearby observations, improving over the baseline 2D-TAN model on Matterport3D, but not on HouseTours. EGO-TOPO reduces the entire video into a single feature using a graph convolutional network, offering redundant information at each time-step which hurts performance on both datasets. Both EPC and our model consistently improve over the baseline, but our model performs the best overall, particularly on the “visit”-style queries where reasoning about the surroundings is required. Our model variants in Table 2 (right) are consistent with ROOM PREDICTION — training from scratch and SSL-based training result in poor performance, while the two local state prediction approaches perform the best.

Our ablation experiments in Supp. show that pose information is essential, that noise during pretraining improves robustness downstream, and contains experiments that study the effect of simulation data volume and memory size.
5 Conclusion

We proposed a framework to learn environment-aware representations from videos that goes beyond capturing what is immediately visible in short video-clips, to encoding the local surroundings of a camera-wearer at each time-step. Despite challenging sim-to-real conditions, our experiments on real-world videos for predicting visited rooms and retrieving important moments from natural language queries demonstrate the value of our human-centric environment understanding approach. While our focus thus far is on environment-relevant tasks, future work can go beyond querying walkthrough-like videos and leverage such representations to contextualize human actions and object interactions to support downstream AR applications like action forecasting, or to help embodied robot agents learn better from human demonstrations in similar environments.

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Supplementary Material

This section contains supplementary material to support the main paper text. The contents include:

- (§S1) Videos illustrating the local state prediction task in Sec. 3.2 and the downstream video tasks in Sec. 3.3.
- (§S2) Additional walkthrough collection details to supplement Sec. 4.1.
- (§S3) Data annotation, processing details and analysis for both datasets in Sec. 4.1.
- (§S4) Camera-pose estimation details using COLMAP for our method described in Sec. 3.3.
- (§S5) Architecture and training details for all models in Sec. 4.4.
- (§S6) Architecture and training details for the VANILLA downstream video models in Sec. 4.6 and Sec. 4.7.
- (§S7) Results for EPISODIC MEMORY sweeping over the full range of IoU values to supplement results in Table 2.
- (§S8) Ablation experiments for model design choices.
- (§S9) Additional attention visualization results to supplement Fig. 5.
- (§S10) Additional details about entropy and instance difficulty in the ROOM PREDICTION task from Sec. 4.6.
- (§S11) Details about rare instances during pretraining following discussion in Sec. 3.2.

S1 Videos illustrating the local state prediction task and downstream tasks

In the first part of the video, we demonstrate the local state prediction task from Sec. 3.2 of the main paper. The video shows the first-person view of the camera-wearer (left panel). The right panel shows the top-down view of the environment with the agent trajectory (blue gradient) and nearby objects (colored squares). Note that models only see the egocentric view — the top-down map is for illustration only. Given a simulated video walkthrough and a query time-stamp, the model must predict the direction of each object near it. Correct, missing and false positive predictions are shown for each direction (left panel). Correct predictions on the top-down map are highlighted in cyan.

In the second part of the video, we show examples of the two downstream video tasks from Sec. 3.3 of the main paper, on both the Matterport3D and HouseTours datasets. In the ROOM PREDICTION examples, the model must predict which room the camera-wearer is in from a short clip. As mentioned in Sec. 4.6, the clips show quick motions and often contain ambiguous views making it hard to predict room labels directly using traditional scene recognition methods. For example, the “staircase” is not visible as the person descends it (HouseTours, bottom right video). In the EPISODIC MEMORY examples, the model must predict the moment in time that answers a particular environment-centric query. The video examples show how this requires reasoning about the
camera-wearer’s surroundings. For example, in the second last clip (“when did I visit the sink in the bathroom?”) the sink is only seen briefly in the video but the response requires the window of time that the camera-wearer was physically near it (within arms reach) regardless of visibility.

S2 Walkthrough generation details

As mentioned in Sec. 4.1 of the main paper, we generate simulated walkthroughs in Gibson [84] scenes to train our models. Given an environment, we first cluster all navigable points using KMeans, selecting between 4-64 clusters depending on the environment size. With each cluster centroid as a starting location, we sample 8-16 nearest goal locations, shuffle them (to allow re-visitation), and make an agent visit the goals in sequence. We use a shortest-path planning agent that uses the underlying navigation graph to reach goals in the fewest number of steps. We collect a dataset of ~50k episodes, each of 512-timesteps, of our agents visiting such goal sequences for experiments in Sec. 3.2. Fig. S1 shows a random sample of walkthroughs.

Note that the walkthroughs are generated in environments where objects are not moved, however a large part of our real-world environments are in fact static. This includes static scene elements like doors, windows, counter tops, staircases, and most objects that are typically not moved like refrigerators, beds, couches, TV sets. Encoding these objects and scene elements can thus still provide value for human-centric environment understanding, even when some objects may have moved around.
Table S1: Dataset train / val / test splits. Splits based on scenes and instances are shown. Gibson is used only for pretraining (Sec. 3.2).

| Environments | Room prediction | Episodic memory |
|--------------|-----------------|-----------------|
| Gibson [84]  | 64 / 17 / –     | –               |
| Matterport3D [7] | 57 / 6 / 21     | 7790 / 1088 / 3302 | 11033 / 1055 / 4258 |
| HouseTours [8] | 570 / 135 / 181 | 14093 / 3462 / 4938 | 2010 / 462 / 706 |

Table S2: Room taxonomies for Matterport3D and HouseTours

| Matterport3D       | HouseTours         |
|--------------------|--------------------|
| hallway bathroom   | attic              |
| office living room | dining room family |
| bedroom            | bedroom            |
| closet             | garage/shed        |
| corridor/hallway   | gym                 |
| dining room        | kitchen             |
| driveway           | lawn/yard/garden   |
| front door/entrance| living room         |
| attic              | office/home office |
| balcony            | porch               |
| basement           | recreation room     |
| dining room         | (billiards room/play room) |
| bedroom            | staircase           |
| closet             | storage/laundry/utility room |
| garage/shed        | swimming pool      |

S3 Data collection and annotation details

As mentioned in Sec. 4.1 of the main paper, we collect labels for each video dataset. For Matterport3D, we directly use the ground truth information available through the simulator to extract labels. For HouseTours, we crowd-source annotations. We describe the data collection process and present data statistics for each dataset and task. The resulting dataset distribution can be seen in Table S1.

S3.1 Annotation requirements for downstream tasks

**Room prediction** For this task, room labels are required at each time-step of the video. The 9 room categories used in Matterport3D are in Table S2 (left). These categories are pre-defined in the simulator. The 21 room categories used in HouseTours are in Table S2 (right). These categories were generated manually from a combination of Matterport3D room categories and a relevant subset of Places365 categories corresponding to indoor scenes.

**Episodic memory** For this task, natural language queries and corresponding moment boundaries (start and end times) are required. We define 7 query templates where o refers to objects and r refers to rooms: “see o”, “see o in r”, “see o1 then o2”, “visit r1 then r2”, “visit o/r”, “visit o1 then o2”, “visit o in r”. Each template captures a type of question that requires a different mechanism of reasoning. “see” queries require reasoning about what is immediately visible; “visit” queries require an understanding of where the camera-wearer is in the environment and what objects are nearby (within arms reach); “see/visit o1 then o2” and “see/visit o in r” require both spatial and temporal reasoning. Natural language queries follow from these templates. For example, for the “visit r1 then r2” template, a natural language query may be “When did I first walk from the kitchen to the bathroom?”. The list of query templates, examples and descriptions can be seen in Table S3. The task definition follows prior work [27] but is adapted for the datasets used, and contains more environment-centric queries.

Our video in Sec. S1 shows examples of both tasks to complement the image examples from Fig. 4 of the main paper. The video highlights the stark contrast
between prediction in static images (third-person photos) which contains well-framed images that are easy to recognize, and egocentric video which is much more challenging. In this setting, video is tied to quick ego-motion as the camerawearer moves around the environment and objects are seen only briefly (or not at all) in non-canonical viewpoints.

### S3.2 Matterport3D annotations

For ROOM PREDICTION, navigable location are mapped to room categories using information from the simulator. We map agent positions for each video frame to these categories. For EPISODIC MEMORY we use room labels and extracted object positions to generate queries from the 7 templates above. We define objects as “seen” if they occupy at least 5% of the pixels in a given frame. We define objects as “visited” if the agent is $< 1.0m$ from the object, regardless of its visibility, following embodied navigation protocol (ObjectNav [3]). Rooms are “visited” using the position $\rightarrow$ room category mapping above. We generate queries for each template by tracking objects and rooms that are seen and visited over time. If there are multiple visitations to an object or room, we ensure unique responses to queries by adapting them to consider only the first (or last) visit.

Fig. S2 shows annotation statistics for both tasks on Matterport3D. Trajectories are fixed length (256 steps) with 4 room transitions on average. HouseTours videos are variable length with 6 room transitions on average. Both visits and moments are short, making it difficult to localize the response to the natural language query, and providing little extra context to recognize rooms. See our video in Sec. S1 for examples.

### S3.3 HouseTours annotations

We crowd-source annotations for real-world videos from HouseTours. For ROOM PREDICTION, we ask annotators to watch a video and mark the start and end time of each “visit” to a room. They must then label each visit with one of

| Template | Example | Description |
|----------|---------|-------------|
| see $o$  | Where did I first see the remote control? | Objects must be visible for the moment duration |
| see $o$ in $r$ | When did I see the mirror in the bathroom? | Object must be physically inside the room |
| see $o_1$ then $o_2$ | Where did I see a table then a chair? | Objects can either be seen together or in quick succession |
| visit $r_1$ then $r_2$ | When did I walk from the living room to the kitchen? | Start = when the person begins to leave; End = they are fully inside the kitchen. |
| visit $o/r$ | When did I last visit the couch?; When did I last visit the bedroom? | Visit = physically near an object (within arms reach) or physically inside a room |
| visit $o_1$ then $o_2$ | When did I visit the lamp then the couch? | Same as see $o_1$ then $o_2$, but using the “visit” criteria above |
| visit $o$ in $r$ | When did I visit the mirror in the bathroom? | Same as see $o_1$ in $o_2$, but using the “visit” criteria above |

Table S3: Query templates and examples for the Episodic memory task.
the 21 room categories (from Table S2, right). An illustration of the annotation interface is shown in Fig. S4.

For Episodic memory, we ask annotators to identify an interesting moment (e.g., where a person sees a salient object, moves from one room to another, visits an important object) which serves as the answer to a query. The moment is specified by a start and end time, while the query is specified as natural language text generated following one of the 7 template classes from Table S3. An illustration of the annotation interface is shown in Fig. S5.

Fig. S3 shows annotation statistics for both tasks on HouseTours. In general, trajectories are relatively shorter than Matterport3D, though they involve more room transitions (6 on average). They share similar challenges with short moments. See our video in Sec. S1 for examples.

S4 Camera pose estimation on HouseTours data

As mentioned in Sec. 3.3 of the main paper, we run COLMAP [67], a structure from motion framework, to compute camera-pose information associated with each frame of the video. For this, we first extract frames from each video at 2fps. Then we run COLMAP using a precomputed vocabulary tree file (flickr100K_words32K).
The resulting trajectories are inherently noisy due to the approximate nature of the SfM pipeline and the absence of true camera parameters for such in-the-wild video. We post-process them by removing erroneous pose values (ones that cause jumps in pose atypical to smooth motion).

Overall, COLMAP successfully localizes ~32 hours of video from 886 houses out of the original 119 hours available in [8]. Some examples of video trajectories are shown in Fig. S6. Comparing these to the simulated trajectories in Fig. S1, we see smoother trajectories overall, but with unrealistic jumps in localizations and loop-closure failures. Note that we visualize only the trajectory, not obstacles in the environment, as we do not have access to occupancy maps for the real-world videos.

S5 Architecture and training details (pretraining)

We present additional details for our model in Sec. 3 of the main paper, as well as the baselines in Sec. 4.4. The full list of hyperparameters are in Table S5.

Environment encoder $E$ and decoder $D$. We build on the transformer [76] architecture for our model. The input to the encoder $f \in \mathbb{R}^{2048}$ are features
Fig. S4: Annotation interface for collecting Room prediction labels. Annotators must densely segment room visits (start and end times) and associate a class label to each of them.

Fig. S5: Annotation interface for collecting Episodic memory labels. Annotators must identify an interesting moment in time (start and end time) and associate a query template, a natural language query and object/room labels that fill the query template slots.
from an ImageNet-pretrained ResNet-50. First, we transform these features to a 128-dimension vector. Relative pose is a 4-dimensional vector $(x, z, \sin \theta, \cos \theta)$ where $(x, z)$ is the relative position, and $\theta$ is the relative heading of the observation. We sample noise from a uniform distribution between $[-0.0125, 0.0125]$ for position, and $[-0.157, 0.157]$ for heading and add it to pose at each time-step. This pose information is then embedded into a 16-dimensional vector. These are concatenated with the visual embedding, and then transformed back to a 128-dimension vector using $M_p$. Sin-cosine position embeddings are added to this input following [76] resulting in the transformer input $\{x_1, ..., x_N\}$ in Equation 2.

The encoder $E$ performs multi-headed self-attention using these inputs, with 2 layers, 8 heads and hidden dimension 128. The decoder $D$ is a 2-layer transformer with hidden dimension 128 which attends to the outputs of $E$ to generate the output representation. We predict relative directions for the top-20 most frequent object classes from Gibson (see Table S4). We use the transformer implementation from PyTorch [56].

Our architecture is similar to prior embodied navigation approaches [59, 22] but includes the environment decoder that queries the memory based on pose and visual content, and is trained using our proposed learning objective in Sec. 3.2. See Table S5 (left).

![Fig. S6: Camera-pose for HouseTours from COLMAP. The blue gradient represents the trajectory from start (white) to end (blue).](image)
**EPC architecture details.** EPC [59] is a transformer encoder-decoder model that masks out frames from physical locations and predicts the features of these masked zones given a query pose. We generate graphs to train this baseline following their approach.

Specifically, for every video frame \( \{ f_1, ..., f_T \} \), we compute the geometric viewpoint overlap with every other frame. The viewpoint overlap \( \psi(f_i, f_j) \) is calculated by projecting pixels from the frames to 3D point-clouds using camera intrinsics, agent pose and depth measurements, and measuring the percentage of shared points across frames. We use \( \psi(f_i, f_j) \) as our distance metric to cluster all frames in video into zones using hierarchical agglomerative clustering. We set the distance threshold to 0.8 as larger values result in too few zones.

We sample 4 unseen zones per instance in a batch of which one is “positive” and three are “negatives” for contrastive learning. We collect negatives from all instances in a batch during training. The network is trained using noise-contrastive estimation following [59]. See Table S5 (center).

**Ego-Topo architecture details.** Ego-Topo [53] is an approach to translate egocentric video frames into a topological graph, where each node contains a list of clips that correspond to a physical location, and edges correspond to rough spatial layout.

Since we have pose information, we directly use it to determine whether two frames belong to the same zone or not (i.e., we do not train a retrieval network to approximate this). This amounts to a clustering of the trajectory based on pose (position and heading) and represents an enhanced version of Ego-Topo that benefits from pose data. We use affinity propagation to cluster frames into nodes. To compute edges, we calculate the distance between the centroid of each node and assign an edge if this distance is < 3.0m to be consistent with Equation 1.

Node features are calculated as the average of features assigned to that node. We use a 2-layer graph convolutional neural network (GCN) to aggregate features across nodes, and then average them to form a single video encoding following [53]. See Table S5 (center).

**Training details.** As mentioned in Sec. 4.3 of the main paper, we train our models for 200 epochs using the Adam optimizer with learning rate \( 1e^{-4} \). We sample \( K = 32 \) frames to construct our memory. At training, we sample frames from the video but randomly offset frame indices to train robust models. During inference, we uniformly sample frames. We select the model with the lowest validation loss to evaluate downstream. See Table S5 (right) for all optimization hyperparameters.

**S6 Architecture and training details (downstream)**

We present additional details for the approaches in Sec. 3.3 of the main paper. The full list of hyperparameters are in Table S6.

**Room prediction models.** As mentioned in Sec. 4.6 of the main paper, for our baseline VANILLA model, we build on the wide ResNet-18 model from [88]. We
use the authors existing code and their provided pretrained models to initialize the model. The classifier head is a 2-layer MLP with hidden dimension 512. The backbone is frozen and only the classifier is fine-tuned. \( N = 8 \) frames around the target frame are used to provide additional context. The features are max-pooled before classification.

For our models, we use the target frame as the query to produce a single environment-feature, which is then concatenated with all \( N = 8 \) frames and aggregated following Equation 6. This new, enhanced input is fed into the VANILLA model as described above.

We train all models for 30 epochs on Matterport3D [7] and 50 epochs on HouseTours [8] with learning rate \( 1e^{-4} \) using the Adam optimizer. The full list of hyperparameters are in Table S6 (left)

### Episodic memory retrieval models.
As mentioned in Sec. 4.7 of the main paper, for our baseline VANILLA model, we build on the 2D-TAN model from [86]. We use an existing implementation based on the authors original code. Visual inputs are encoded as \( N = 256 \) clip features, created by adaptive average pooling of image features from a ResNet-50 model pretrained on ImageNet. The natural language query is encoded using a 2-layer LSTM model. The visual and language features are provided to the 2D-TAN model to generate moment predictions. Please see the original paper for the model workflow [86].

For our models, we select the center frame of each of the \( N = 256 \) inputs and use them as query frames to produce \( N = 256 \) environment features. Each pair of input feature and environment feature are aggregated following Equation 6, and then input to the 2D-TAN model described above.

We train all models for 60 epochs on both datasets with a learning rate of \( 1e^{-3} \) using the Adam optimizer. The full list of hyperparameters are in Table S6 (right)

### Additional experiments and ablations for Episodic memory

In Sec. 4.7 of the main paper, we measure model performance using the Rank1@0.3 metric. We show results across multiple IoU thresholds \( m = \{0.1, 0.3, 0.5, 0.7\} \)
in Table S7. Our model outperforms all baselines on a majority of the metrics, and performs best on the most strict metric (Rank1@0.7) which demands high overlap with the ground truth moment.

Next, in Table S8 we show a breakdown of model performance by individual query type to expand on the results in Table 2 where we roughly categorize queries as either “visit” and “see” queries. On Matterport3D, our approach performs worse on the “see” queries but outperforms baselines on most “visit” queries, and overall considering all queries. On HouseTours, our approach greatly performs all methods on nearly all query types (except for “see o” and “visit o in r”). Note that the number of instances vary per query type. This makes scores for query types with only a few instances unreliable. The overall performance across all query types (or groups of query types) is more reliable, and is what we report in Table 2.

S8 Ablations experiments

We study several design choices and their impact on pretraining and downstream performance. We report mean average precision (mAP) across all direction classes, and downstream performance metrics for ROOM PREDICTION and EPISODIC MEMORY in Table S9.

**Importance of pose information.** We train models with different pose requirements in Table S9 (a) Models that do not use any pose information struggle to perform well at pretraining. Models that use raw pose values (not relative to the query) are unable to link the query observation to this memory. The relative pose between each observation and the query is essential to train our models,
Table S7: Episodic memory retrieval results over multiple IoU thresholds. Results are averaged across three runs.

Table S8: Episodic memory retrieval results by query type on Matterport3D (top) and HouseTours (bottom) o and r represent objects and rooms respectively. These categories match the templates in Table S3. Results in blue are second best. Results are averaged across three runs.

which agrees with recent embodied navigation studies [22, 59]. This performance is correlated with downstream accuracy when fine-tuned for each task (columns 2 and 3). Additionally, we test the effect of noise in pose. w/o NOISE in Table S9 (a) shows that for a similar pretraining performance, including noise results in small improvements.

Effect of simulation data volume. We experiment with the number of walkthroughs W used for pretraining in Table S9 (b). We select walkthroughs in a round-robin manner from each scene to avoid oversampling from a single environment. More walkthroughs results in the best transfer, indicating that diversity in paths travelled — even when sampled from a limited set of environments — still adds value for training our models.

Effect of memory size. In Table S9 (c) we vary the memory size K sampled for our environment encoder in Sec. 3.2. A larger memory size implies larger coverage of environment views, which results in small improvements on the pretraining
Table S9: Ablation studies. (a) Importance of pose information and effect of noise. (b) Effect of simulation data volume. (d) Effect of memory size. Results are averaged over three runs. MP = Matterport3D, HT = HouseTours.

A task but does not significantly affect downstream performance and comes at a significant additional training cost.

S9 Additional attention visualizations

We present additional examples visualizing the learned attention values in our transformer decoder model in Fig. S9 to supplement Fig. 5 of the main paper. Our model learns to attend to diverse views that are not simply based on temporal adjacency or visual overlap — they capture the surroundings of the camera-wearer.

S10 Easy vs. Hard instances in the Room prediction task

As mentioned in Sec. 4.6 of the main paper, we split instances into easy vs. hard for evaluation based on the prediction entropy of a pre-trained scene classifier model. In Fig. S7, we show the distribution of this entropy score across both Matterport3D and HouseTours data. In general, Matterport contains harder instances as the agent quickly transitions from one room to another. We show examples of easy vs. hard instances in Fig. S8. Note that the figure only shows the center frame of the clip that is used to predict the room label to highlight the difference between easy and hard frames. See our video in Sec. S1 for more context.

S11 Memory vs. anticipation during pretraining

As mentioned in Sec. 3.2 of the main paper, our pretraining task involves elements of both aggregating information about relevant views spread across the
Fig. S7: Distribution of entropy scores for Matterport3D and HouseTours instances.

Fig. S8: Illustration of easy vs. hard instances from Matterport3D and HouseTours. Following Sec. 4.6, we define hard instances as those with entropy score $S$ higher than the top 30% instances in Matterport3D.
Fig. S9: Visualized attention weights. Following Fig. 5, the query frame (top left) and top-3 attended views (colored boxes), their positions along the trajectory (colored circles), and their associated attention scores are shown.

walkthrough, as well as anticipating objects that are rarely (or never seen). We quantify this statement in Fig. S10 where we show the percentage of training instances where objects are rarely seen, for different definitions of rarity. For example, 23% of training instances involve predicting objects that appear in only $k < 4$ frames. 5% of training instances involve anticipating completely unseen object instances ($k < 1$).
Fig. S10: Percentage of training instances that involve “rare” objects. The x-axis sets a threshold for what is considered rare. For example, 5% of training instances involve anticipating completely unseen object instances ($k < 1$).