# Agent-to-Sim: Learning Interactive Behavior Models from Casual Longitudinal Videos

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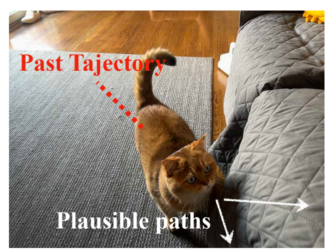
## Abstract

We present Agent-to-Sim (ATS), a framework for learning interactive behavior models of 3D agents in a 3D environment from casually-captured videos. Different from prior works that rely on marker-based tracking and multiview cameras, ATS learns natural behaviors of animal and human agents in a *non-invasive* way, directly from monocular video collections. Modeling 3D behavior of an agent requires persistent 3D tracking (e.g., knowing which point corresponds to which) over a long time period. To obtain such data, we develop a coarse-to-fine registration method that tracks the agent and the camera over time through a canonical 3D space, resulting in a complete and persistent spacetime 4D representation. We then train a generative model of agent behaviors using paired data of perception and motion of an agent queried from the 4D reconstruction. ATS enables real-to-sim transfer of agents in their familiar environments given longitudinal video recordings (e.g., over a month). We demonstrate results on pets (e.g., cat, dog, bunny) and human given monocular RGBD video collections captured by a smartphone.

## 1 Introduction




Consider an image on the right: where will the cat go and how will it move? Having seen cats interacting with the environment and people many times, we know that cats often go to the couch and follow humans around, but run away if people come too close. Such a model of a physical agent is what enables plausible behavior simulation. Our goal is to learn such interactable behavior models of agents from videos. This is a fundamental problem with practical application in content generation for VR/AR, robot planning in safety-critical scenarios, and behavior imitation from the real world (Park et al., 2023; Ettinger et al., 2021; Puig et al., 2023; Srivastava et al., 2022; Li et al., 2024).

On one hand, prior works (Cao et al., 2020; Bajcsy et al., 2023; Rempe et al., 2023) utilize trajectory computed by path-planning algorithms or hand-designed logic from game simulators (Van Den Berg et al., 2011; Hart et al., 1968). While these approaches benefit from high-quality trajectory data paired with perfect object and scene geometries, it is laborious to manually craft simulators that suit the needs of each type of application, and the data distribution is fundamentally different from the real world, leading to unnatural motion and interactions. On the other hand, motion capture systems enable collecting behavior data in a limited and controlled setup, such as autonomous driving (Ettinger et al., 2021), human motion (Mahmood et al., 2019; Joo et al., 2017), and how they interact with objects/scenes (Hassan et al., 2021; Kim et al., 2024). However, such capture systems are cumbersome and do not scale well to the full spectrum of natural behavior one may care about, such as the behavior of animals, casual events, and long-term activities.

In a step towards building faithful agent simulators in a scalable and non-invasive way, we present ATS (Agent-to-Sim), a framework for learning interactive behavior models of 3D agent in a 3D environment from *casual videos*, as shown in Fig. 1. It enables 3D-fying behavior data in a casual setup (*e.g.*, with a smartphone), and provides paired training data of perception and motion of an agent that is grounded in a natural environment.

Advances in 3D reconstruction (Song et al., 2023; Mildenhall et al., 2020; Kerbl et al., 2023; Gao et al., 2022; Park et al., 2021; Guo et al., 2023; Weng et al., 2022) and 3D pose estimation (Ye et al.,

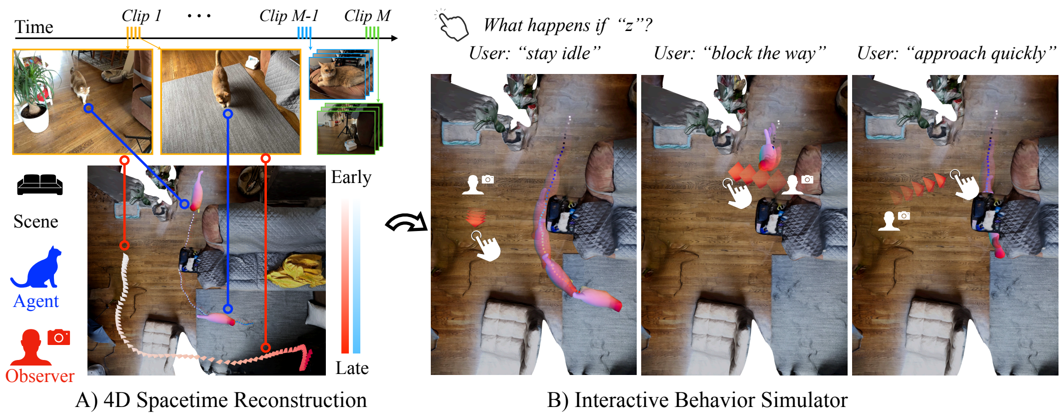
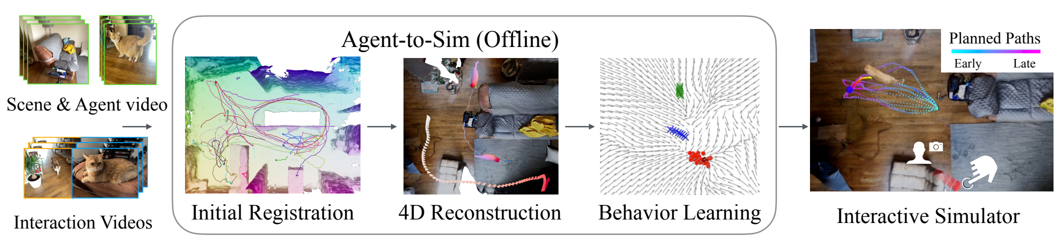



Figure 1: **Learning agent behavior from longitudinal casual video recordings.** We answer the following question: can we simulate the behavior of an agent, by learning from casually-captured videos of the *same* agent recorded across a long period of time (*e.g.*, a month)? A) We first reconstruct videos in 4D (3D & time), which includes the scene, the trajectory of the agent, and the trajectory of the observer (i.e., camera held by the observer). Such individual 4D reconstructions are registered across time, resulting in a *complete* and *persistent* 4D representation. B) Then we learn a model of the agent for interactive behavior generation. The behavior model explicitly reasons about goals, paths, and full body movements conditioned on the agent's ego-perception and past trajectory. Such an agent representation allows generation of novel scenarios through conditioning. For example, conditioned on different observer trajectories, the cat agent chooses to walk to the carpet, stays still while quivering his tail, or hide under the tray stand. *Please see videos results in the supplement.*

2023; Yuan et al., 2022; Kocabas et al., 2023; Pavlakos et al., 2022) provide a pathway to obtain high-quality models of scenes and agents from monocular videos. Despite the ability to 3D-fy a single video or image collections of hundreds of frames, none of them can reconstruct a *complete* and *persistent* (Chai et al., 2023) 4D representation from orders of magnitude more data, e.g., 20k frames of videos, which is crucial for learning agent behavior. We introduce a novel coarse-to-fine registration approach that re-purposes large image models, such as DiNO-v2 (Oquab et al., 2023), as neural localizers, which register the cameras with respect to canonical spaces of both the agent and the scene. This allows us to extend an earlier work (Song et al., 2023) to build a complete and persistent 4D representation containing the agent, the scene, and the observer given a large collection of casual RGBD videos. With this, an interactive behavior model can be learned by querying paired ego-perception and motion data of an agent from the 4D reconstruction.




The resulting framework, ATS, can simulate interactive behaviors like those described at the start: agents like pets that leap onto furniture, dart quickly across the room, timidly approach nearby users, and run away if approached too quickly. Our contributions are summarized as follows:

1. **4D from Video Collections.** We build persistent and complete 4D representations from a collection of casual videos, accounting for deformations of the agent, the observer, and changes of the scene across time, enabled by a coarse-to-fine registration method.

2. **Interactive Behavior Generation.** ATS learns behavior that is *interactive* to both the observer and 3D scene. We show results of generating plausible animal and human behaviors reactive to the observer's motion, and aware of the 3D scene.

3. **Agent-to-Sim (ATS) Framework.** We introduce a real-to-sim framework to learn simulators of interactive agent behavior from casually-captured videos. ATS learns natural agent behavior, and is scalable to diverse scenarios, such as animal behavior and casual events.

## 2 Related Works

**4D Reconstruction from Monocular Videos.** Reconstructing time-varying 3D structures from monocular videos is challenging due to its under-constrained nature. Given a monocular video, there are multiple different interpretations of the underlying 3D geometry, motion, appearance, and lighting (Szeliski & Kang, 1997). As such, previous methods often rely on category-specific 3D prior (*e.g.*, 3D humans) (Goel et al., 2023; Loper et al., 2015; Kocabas et al., 2020) to deal with the ambiguities. Along this line of work, there are methods to align reconstructed 3D humans to the world coordinate with the help of SLAM and visual odometry (Ye et al., 2023; Yuan et al., 2022; Kocabas et al., 2023). Sitcoms3D (Pavlakos et al., 2022) reconstructs both the scene and human parameters, while relying on shot changes to determine the scale of the scene. However, the use of parametric body models limits the degrees of freedom they can capture, and makes it difficult to reconstruct agents from arbitrary categories which do not have a pre-built body model, for example, animals. Another line of work (Yang et al., 2022; Wu et al., 2021) avoids using category-specific 3D priors and optimizes the shape and deformation parameters of the agent given pixel priors (*e.g.*, optical flow and object segmentation), which works well for a broad range of categories including human, animals, and vehicles. TotalRecon (Song et al., 2023) further takes into account the background scene, such that the motion of the agent can be decoupled from the camera and aligned to the world space. However, most of the method operates on a few hundreds of frames, and none of them can reconstruct a complete 4D scene while obtaining persistent 3D tracks over orders of magnitude more data (e.g., 20k frames of videos). We develop a coarse-to-fine registration method to register the agent and the environment into a canonical 3D space, which allows us to leverage large-scale video collection to build agent behavior models.

**Behavior Prediction and Generation.** Behavior prediction has a long history, starting from simple physics-based models such as social forces (Helbing & Molnar, 1995; Alahi et al., 2016) to more sophisticated "planning-based" models that cast prediction as reward optimization, where the reward is learned via inverse reinforcement learning(Kitani et al., 2012; Ziebart et al., 2009; Ma et al., 2017; Ziebart et al., 2008). With the advent of large-scale motion data, generative models have been used to express behavior multi-modality (Mangalam et al., 2021; Salzmann et al., 2020; Choi et al., 2021; Seff et al., 2023; Rhinehart et al., 2019). Specifically, diffusion models are used for behavior modeling for being easily controlled via additional signals such as cost functions (Jiang et al., 2023) or logical formulae (Zhong et al., 2023). However, to capture plausible behavior of agents, they require diverse data collected in-the-wild with associated scene context, *e.g.*, 3D map of the scene (Ettinger et al., 2021). Such data are often manually annotated at a bounding box level (Girase et al., 2021; Ettinger et al., 2021), which limits the scale and the level of detail they can capture.

**3D Agent Motion Generation.** Beyond autonomous driving setup, existing works for human and animal motion generation (Tevet et al., 2022; Rempe et al., 2023; Xie et al., 2023; Shafir et al., 2023; Karunratanakul et al., 2023; Pi et al., 2023; Zhang et al., 2018; Starke et al., 2022; Ling et al., 2020; Fussell et al., 2021) have been primarily using simulated data (Cao et al., 2020) or motion capture data collected with multiple synchronized cameras (Kim et al., 2024; Mahmood et al., 2019; Hassan et al., 2021; Luo et al., 2022). Such data provide high-quality body motion, but the interactions of the agents with the environment are either restricted to a flat ground, or a set of pre-defined furniture or objects (Hassan et al., 2023; Zhao et al., 2023; Lee & Joo, 2023; Zhang et al., 2023a; Menapace et al., 2024). Furthermore, the use of simulated data and motion capture data inherently limits the naturalness of the learned behavior, since agents often behave differently when being recorded in a capture studio compared to a natural environment. To bridge the gap, we develop 4D reconstruction methods to obtain high-quality trajectories of agents interacting with a natural environment, with a simple setup that can be achieved with a smartphone.

## 3 APPROACH

ATS learns behavior models of an agent in a 3D environment given RGBD videos. Sec. 3.1 describes our spacetime 4D representation that contains the agent, the scene, and the observer. We fit such 4D representation to a collection of videos in a coarse-to-fine manner, where the camera poses are initialized from data-driven methods and refined through differentiable rendering optimization (Sec. 3.2). Given the 4D reconstruction, Sec. 3.3 trains an behavior model of the agent that is *interactive* to the scene and the observer. We provide a table of notations and modules in Tab. 6-7.

### 3.1 4D REPRESENTATION: AGENT, SCENE, AND OBSERVER

Given many monocular videos, our goal is to build a complete and persistent spacetime 4D reconstruction of the underlying world, including a deformable agent, a rigid scene, and a moving observer. We factorizes the 4D reconstruction into a canonical structure and a time-varying structure.

**Canonical Structure $\mathbf{T} = \{\sigma, \mathbf{c}, \boldsymbol{\psi}\}$.** The canonical structure contains an agent neural field and a scene neural field, which are time-independent. They represent densities $\boldsymbol{\sigma}$, colors $\mathbf{c}$, and semantic features $\boldsymbol{\psi}$ implicitly with MLPs. To query the value at any 3D location $\mathbf{X}$, we have

$$(\sigma_s, \mathbf{c}_s, \boldsymbol{\psi}_s) = \mathrm{MLP}_{scene}(\mathbf{X}, \boldsymbol{\beta}_i), \tag{1}$$

$$(\sigma_a, \mathbf{c}_a, \boldsymbol{\psi}_a) = \mathrm{MLP}_{agent}(\mathbf{X}). \tag{2}$$

The scene field takes in a learnable code $\boldsymbol{\beta}_i$ (Niemeyer & Geiger, 2021) per-video, which can represent scenes of slightly different appearance and layout (across videos) with a shared backbone.

**Time-varying Structure $\mathcal{D} = \{\boldsymbol{\xi}, \mathbf{G}, \mathbf{W}\}$.** The time-varying structure contains an observer and an agent. The observer is represented by the camera pose $\boldsymbol{\xi}_t \in SE(3)$, defined as canonical-to-camera transformations. The agent is represented by a root pose $\mathbf{G}_t^0 \in SE(3)$, defined as canonical-to-camera transformations, and a set of 3D Gaussians, $\{\mathbf{G}_t^b\}_{\{b=1,\dots,25\}}$, referred to as "bones" (Yang et al., 2022). Bones have time-varying centers and orientations but constant scales. Through blend-skinning (Magnenat et al., 1988) with learned forward and backward skinning weights $\mathbf{W}$ (Saito et al., 2021), any 3D location in the canonical space can be mapped to the time $t$ space and vice versa,

$$\mathbf{X}_t = \mathbf{G}^a\mathbf{X} = \left(\sum_{b=1}^{B} \mathbf{W}^b \mathbf{G}_t^b\right)\mathbf{X}, \tag{3}$$

which computes the motion of a point by blending the bone transformations (we do so in the dual quaternion space (Kavan et al., 2007) to ensure $\mathbf{G}^a$ is a valid rigid transformation). The skinning weights $\mathbf{W}$ are defined as the probability of a point assigned to each bone.

**Rendering.** To render images from the 4D representation, we use differentiable volume rendering (Mildenhall et al., 2020) to sample rays in the camera space, map them separately to the canonical space of the scene and the agent with $\mathcal{D}$, and query values (*e.g.*, density, color, feature) from the canonical fields of the scene and the agent. The values are then composed for ray integration (Niemeyer & Geiger, 2021). To optimize the world representation $\{\mathbf{T}, \mathcal{D}\}$, we minimize the difference between the rendered pixel values and the observations, as described later in Sec. 3.2.

### 3.2 OPTIMIZATION: COARSE-TO-FINE MULTI-VIDEO REGISTRATION

Given images from $M$ videos represented by color and feature descriptors (Oquab et al., 2023), $\{\mathbf{I}_i, \boldsymbol{\psi}_i\}_{i=\{1,\dots,M\}}$, our goal is to find a spacetime 4D representation where pixels with the same semantics can be mapped to same canonical 3D locations. Variations of appearance, lighting, and camera viewpoint across videos make it challenging to buil such persistent 4D representation.

We design a coarse-to-fine registration approach that globally aligns the agent and the observer poses to their canonical space, and then jointly optimizes the 4D representation while adjusting the poses locally. Such coarse-to-fine registration avoids bad local optima in the optimization.

**Initialization: Neural Localization.** Due to the evolving nature of scenes across a long period of time (Sun et al., 2023), there exist both global layout changes (*e.g.*, furniture get rearranged) and appearance changes (*e.g.*, table cloth gets replaced), making it challenging to find accurate geometric correspondences (Brachmann & Rother, 2019; Brachmann et al., 2023; Sarlin et al., 2019). With the observation that large image models have good 3D and viewpoint awareness (El Banani et al., 2024), we adapt them for camera localization. We learn a scene-specific neural localizer that directly regresses the camera pose of an image with respect to a canonical structure,

$$\boldsymbol{\xi} = f_\theta(\boldsymbol{\psi}), \tag{4}$$

where $f_\theta$ is a ResNet-18 (He et al., 2016) and $\boldsymbol{\psi}$ is the DINOv2 (Oquab et al., 2023) feature of the input image. We find it to be more robust than geometric correspondence, while being more computationally efficient than pairwise matches (Wang et al., 2023). To learn the neural localizer, we first capture a walk-through video and build a 3D map of the scene. Then we use it to train the neural localizer by randomly sampling camera poses $\mathbf{G}^* = (\mathbf{R}^*, \mathbf{t}^*)$ and rendering images on the fly,

$$\arg\min_\theta \sum_j \left( \| \log(\mathbf{R}_0^T(\theta)\mathbf{R}^*) \| + \|\mathbf{t}_0(\theta) - \mathbf{t}^*\|_2^2 \right), \tag{5}$$

where we use geodesic distance (Huynh, 2009) for camera rotation and $L_2$ error for camera translation.

Similarly, we train a camera pose estimator of the agent. First, we fit dynamic 3DGS (Luiten et al., 2024; Yang et al., 2023a) to a long video of the agent with a complete viewpoint coverage. Then we use the dynamic 3DGS as the synthetic data generator, and train a pose regressor to predict root poses $\mathbf{G}^0$. During training, we randomly sample camera poses, time instances, and apply image space augmentations, including color jittering, cropping and masking.

**Objective: Feature-metric Loss.** To refine the camera registration as well as learn the deformable agent model, we fit the 4D representation $\{\mathbf{T}, \mathcal{D}\}$ to the data $\{\mathbf{I}_i, \boldsymbol{\psi}_i\}_{i=\{1,\ldots,M\}}$ using differentiable rendering. Compared to fitting raw rgb values, feature descriptors from large pixel models (Oquab et al., 2023) are found more robust to appearance and viewpoint changes. Therefore, we model 3D feature fields (Kobayashi et al., 2022) besides colors in our canonical NeRFs (Eq. 1-2), render them, and apply both photometric and featuremetric losses,

$$\min_{\mathbf{T},\mathcal{D}} \sum_t \left( \|I_t - \mathcal{R}_I(t;\mathbf{T},\mathcal{D})\|_2^2 + \|\boldsymbol{\psi}_t - \mathcal{R}_{\boldsymbol{\psi}}(t;\mathbf{T},\mathcal{D})\|_2^2 \right) + L_{reg}(\mathbf{T},\mathcal{D}), \tag{6}$$

where $\mathcal{R}(\cdot)$ is the renderer described in Sec 3.1. The observer (scene camera) and the agent's root pose are initialized from the coarse registration. Using featuremetric errors makes the optimization robust to change of lighting, appearance, and minor layout changes, which helps find accurate alignment across videos. We also apply a regularization term that includes eikonal loss, silhouette loss, flow loss and depth loss similar to Song et al. (2023).

**Scene Annealing.** To reconstruct a complete 3D scene when some videos are a partial capture (*e.g.* half of the room), we encourage the reconstructed scenes across videos to be similar. To do so, we randomly *swap* the code $\boldsymbol{\beta}$ of two videos during optimization, and gradually decrease the probability of applyig swaps from $\mathcal{P} = 1.0 \rightarrow 0.05$ over the course of optimization. This regularizes the model to share structures across all videos, but keeps video-specific details (Fig. 3).

### 3.3 Interactive Behavior Generation

Given the 4D representation, we extract a 3D feature volume of the scene $\boldsymbol{\Psi}$ and world-space trajectories of the observer $\boldsymbol{\xi}^w = \boldsymbol{\xi}^{-1}$ as well as the agent $\mathbf{G}^{0,w} = \boldsymbol{\xi}^w\mathbf{G}^0, \mathbf{G}^{b,w} = \mathbf{G}^{0,w}\{\mathbf{G}^b\}_{\{b=1,\ldots,25\}}$, as shown in Fig. 5. Next, we learn an agent behavior model interactive with the world.

**Behavior Representation.** We represent the behavior of an agent by its body pose in the scene space $\mathbf{G} \in \mathbb{R}^{6B\times T^*}$ over a time horizon $T^* = 5.6$s. We design a hierarchical model as shown in Fig. 2, where the body motion $\mathbf{G}$ is conditioned on path $\mathbf{P} \in \mathbb{R}^{3\times T^*}$, which is further conditioned on the goal $\mathbf{Z} \in \mathbb{R}^3$. Such decomposition makes it easier to learn individual components compared to learning a joint model, as shown in Tab. 4 (a).

**Goal Generation.** We represent a multi-modal distribution of goals $\mathbf{Z} \in \mathbb{R}^3$ by its score function $s(\mathbf{Z}, \sigma) \in \mathbb{R}^3$ (Ho et al., 2020; Song et al., 2020). The score function is implemented as an MLP,

$$s(\mathbf{Z};\sigma) = \mathrm{MLP}_{\theta_\mathbf{Z}}(\mathbf{Z}, \sigma), \tag{7}$$

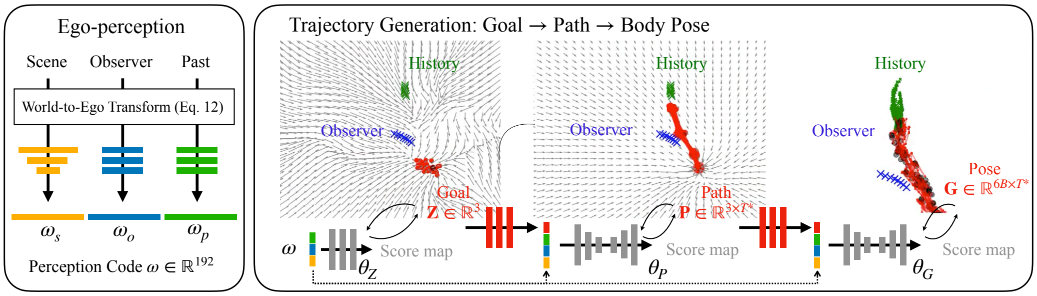



Figure 2: Pipeline for behavior generation. We encode egocentric information into a perception code $\omega$, conditioned on which we generate fully body motion in a hierarchical fashion. We start by generating goals $\mathbf{Z}$, then paths $\mathbf{P}$ and finally body poses $\mathbf{G}$. Each node is represented by the gradient of its log distribution, trained with denoising objectives (Eq. 8). Given $\mathbf{G}$, the full body motion of an agent can be computed via blend skinning (Eq. 3).

trained by predicting the amount of noise $\boldsymbol{\epsilon}$ added to the clean goal, given the corrupted goal $\mathbf{Z} + \boldsymbol{\epsilon}$:

$$\arg\min_{\theta_{\mathbf{Z}}} \mathbb{E}_{\boldsymbol{Z}} \mathbb{E}_{\sigma\sim q(\sigma)} \mathbb{E}_{\boldsymbol{\epsilon}\sim\mathcal{N}(\mathbf{0},\sigma^2\boldsymbol{I})} \left\| \mathrm{MLP}_{\theta_{\mathbf{Z}}}(\boldsymbol{Z}+\boldsymbol{\epsilon};\sigma) - \boldsymbol{\epsilon} \right\|_2^2. \tag{8}$$

**Trajectory Generation.** To generate path conditioned on goals, we represent its score function as

$$s(\mathbf{P};\sigma) = \mathrm{ControlUNet}_{\theta_{\mathbf{P}}}(\mathbf{P},\mathbf{Z},\sigma), \tag{9}$$

where the Control UNet contains two standard UNets with the same architecture (Zhang et al., 2023b; Xie et al., 2023), one taking $(\mathbf{P},\sigma)$ as input to perform unconditional generation, another taking $(\mathbf{Z},\sigma)$ as inputs to inject goal conditions densely into the neural network blocks of the first one. We apply the same architecture to generate body poses conditioned on paths,

$$s(\mathbf{G};\sigma) = \mathrm{ControlUNet}_{\theta_{\mathbf{G}}}(\mathbf{G},\mathbf{P},\sigma). \tag{10}$$

Compared to concatenating the goal condition to the noise latent, this encourages close alignment between the input goal and the path (Xie et al., 2023).

**Ego-Perception of the World.** To generate plausible interactive behaviors, we encode the world *egocentrically* perceived by the agent, and use it to condition the behavior generation. The ego-perception code $\omega$ contains a scene code $\omega_s$, an observer code $\omega_o$, and a past code $\omega_p$, as detailed later. The ego-perception code is concatenated to the noise value $\sigma$ and passed to the denoising networks. Transforming the world to the egocentric coordinates avoids over-fitting to specific locations of the scene (Tab. 4-(b)). We find that a specific behavior can be learned and generalized to novel situations even when seen once. Although there's only one data point where the cat jumps off the dining table, our method can generate diverse motion of cat jumping off the table while landing at different locations (to the left, middle, and right of the table). Please see Fig. 11 for the corresponding visual.

**Scene, Observer, and Past Encoding.** To encode the scene, we extract a latent representation from a local feature volume around the agent, where the volume is queried from the 3D feature volume by transforming the sampled ego-coordinates $\mathbf{X}^a$ using the agent-to-world transformation at time $t$,

$$\omega_s = \mathrm{ResNet3D}_{\theta_\psi}(\boldsymbol{\Psi}_s(\mathbf{X}_w)), \quad \mathbf{X}^w = (\mathbf{G}_t^{0,w})\mathbf{X}^a. \tag{11}$$

where $\mathrm{ResNet3D}_{\theta_\phi}$ is a 3D ConvNet with residual connections, and $\omega_s \in \mathbb{R}^{64}$.

To encode the observer's motion in the past $T' = 0.8$s seconds, we transform observer's trajectories to the ego-coordinate,

$$\omega_o = \mathrm{MLP}_{\theta_o}(\boldsymbol{\xi}^a), \quad \boldsymbol{\xi}^a = (\mathbf{G}_t^{0,w})^{-1}\boldsymbol{\xi}^w, \tag{12}$$

where $\omega_o \in \mathbb{R}^{64}$ represents the observer perceived by the agent. Accounting for the external factors from the "world" enables interactive behavior generation, where the motion of an agent follows the environment constraints and is influenced by the trajectory of the observer, as shown in Fig. 4.

We additionally encode the root and body motion of the agent in the past $T'$ seconds,

$$\omega_p = \mathrm{MLP}_{\theta_p}(\mathbf{G}^{\{0,\ldots,B\},a}), \quad \mathbf{G}^{\{0,\ldots,B\},a} = (\mathbf{G}_t^{0,w})^{-1}\mathbf{G}^{\{0,\ldots,B\},w}. \tag{13}$$

By conditioning on the past motion, we can generate long sequences by chaining individual ones.

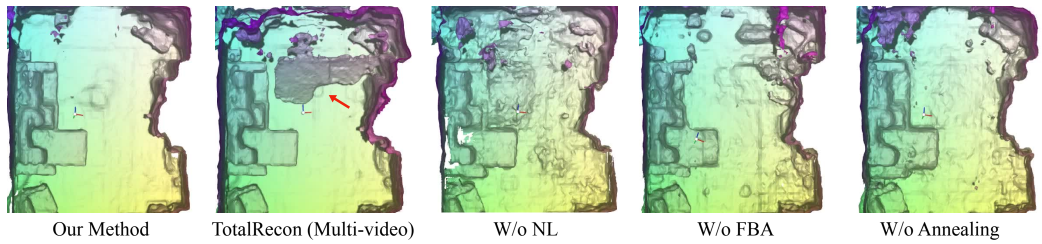



Figure 3: **Comparison on multi-video scene reconstruction**. We show birds-eye-view rendering of the reconstructed scene using the bunny dataset. Compared to TotalRecon that does not register multiple videos, ATS produces higher-quality scene reconstruction. Neural localizer (NL) and featuremetric losses (FBA) are shown important for camera registration. Scene annealing is important for reconstructing a complete scene from partial video captures.

Table 1: **Evaluation of Camera Registration**.

| Method | Rotation Error (°) | Translation Error (m) |
|---|---|---|
| Ours | **6.35** | **0.41** |
| w/o Neural Localizer | 37.59 | 0.83 |
| w/o Featuremetric BA | 22.47 | 1.30 |
| Multi-video TotalRecon | 59.19 | 0.68 |

Table 2: **Dataset used in ATS**.

| | Videos | Length | Unique Days / Span |
|---|---|---|---|
| Cat | 23 | 25m 39s | 9 / 37 days |
| Human | 5 | 9m 27s | 2 / 4 days |
| Dog | 3 | 7m 13s | 1 / 1 day |
| Bunny | 2 | 1m 48s | 1 / 1 day |

## 4 Experiments

**Dataset.** We collect a dataset that emphasizes interactions of an agent with the environment and the observer. As shown in Tab. 2, it contains RGBD iPhone video collections of 4 agents in 3 different scenes, where human and cat share the same scene. The dataset is curated to contain diverse motion of agents, including walking, lying down, eating, as well as diverse interaction patterns with the environment, including following the camera, sitting on a coach, etc.

### 4.1 4D Reconstruction of Agent & Environment

**Implementation Details.** We take a video collection of the same agent as input, and build a 4D reconstruction of the agent, the scene, and the observer. We extract frames from the videos at 10 FPS, and use off-the-shelf models to produce augmented image measurements, including object segmentation (Yang et al., 2023b), optical flow (Yang & Ramanan, 2019), DINOv2 features (Oquab et al., 2023). We use AdamW to first optimize the environment with feature-metric loss for 30k iterations, and then jointly optimize the environment and agent for another 30k iterations with all losses in Eq. 6. Optimization takes roughly 24 hours. 8 A100 GPUs are used to optimize 23 videos of the cat data, and 1 A100 GPU is used in a 2-3 video setup (for dog, bunny, and human).

**Results of Camera Registration.** We evaluate camera registration using GT cameras estimated from annotated 2D correspondences. A visual of the annotated correspondence and 3D alignment can be found in Fig. 12. We report camera translation and rotation errors in Tab. 1. We observe that removing neural localization (Eq. 4) produces significantly larger localization error (e.g., Rotation error: 6.35 vs 37.56). Removing feature-metric bundle adjustment (Eq. 5) also increases the error (e.g., Rotation error: 6.35 vs 22.47). Our method outperforms multi-video TotalRecon by a large margin due to the above innovations.

A visual comparison on scene registration is shown in Fig. 3. Without the ability to register multiple videos, TotalRecon produces protruded and misaligned structures (as pointed by the red arrow). In contrast, our method reconstructs a single coherent scene. With featuremetric alignment (FBA) alone but without a good camera initialization from neural localization (NL), our method produces inaccurate reconstruction due to inaccurate global alignment in cameras poses. Removing FBA while keeping NL, the method fails to accurately localize the cameras and produces noisy scene structures. Finally, removing scene annealing procures lower quality reconstruction due to the partial capture.

Table 3: **Evaluation of 4D Reconstruction**. SV: Single-video. MV: Multi-video.

| Method | DepthAcc (all) | DepthAcc (fg) | DepthAcc (bg) | LPIPS (all) | LPIPS (fg) | LPIPS (bg) |
|---|---|---|---|---|---|---|
| Ours | **0.708** | **0.695** | **0.703** | **0.613** | **0.609** | **0.613** |
| SV TotalRecon | 0.533 | 0.685 | 0.518 | 0.641 | 0.619 | 0.641 |
| MV TotalRecon | 0.099 | 0.647 | 0.053 | 0.634 | 0.666 | 0.633 |

Table 4: **End-to-end Evaluation of Interactive Behavior Prediction.** We report results of predicting goal, path, orientation, and joint angles, using $K = 16$ samples across $L = 12$ trials. The metrics are minimum average displacement error (minADE) with standard deviations ($\pm\sigma$). The lower the better and the best results are in bold.

| Method | Goal (m) ↓ | Path (m) ↓ | Orientation (rad) ↓ | Joint Angles (rad)↓ |
|---|---|---|---|---|
| Location prior (Ziebart et al., 2009) | $0.663^{\pm0.307}$ | N.A. | N.A. | N.A. |
| Gaussian (Kendall & Gal, 2017) | $0.942^{\pm0.081}$ | $0.440^{\pm0.002}$ | $1.099^{\pm0.003}$ | $0.295^{\pm0.001}$ |
| ATS (Ours) | $\mathbf{0.448}^{\pm0.146}$ | $\mathbf{0.234}^{\pm0.054}$ | $\mathbf{0.550}^{\pm0.112}$ | $\mathbf{0.237}^{\pm0.006}$ |
| (a) hier→1-stage (Tevet et al., 2022) | $1.322^{\pm0.071}$ | $0.575^{\pm0.026}$ | $0.879^{\pm0.041}$ | $0.263^{\pm0.007}$ |
| (b) ego→world (Rhinehart & Kitani, 2016) | $1.164^{\pm0.043}$ | $0.577^{\pm0.022}$ | $0.873^{\pm0.027}$ | $0.295^{\pm0.006}$ |
| (c) w/o observer $\omega_o$ | $0.647^{\pm0.148}$ | $0.327^{\pm0.076}$ | $0.620^{\pm0.092}$ | $0.240^{\pm0.006}$ |
| (d) w/o scene $\omega_s$ | $0.784^{\pm0.126}$ | $0.340^{\pm0.051}$ | $0.678^{\pm0.081}$ | $0.243^{\pm0.007}$ |

**Results of 4D Reconstruction.** We evaluate the accuracy of 4D reconstruction using synchronized videos captured with two moving iPhone cameras looking from opposite views. The results can be found in Tab. 3. We compute the GT relative camera pose between the two cameras from 2D correspondence annotations. One of the synchronized videos is used for 4D reconstruction, and the other one is used as held-out test data. For evaluation, we render novel views from the held-out cameras and compute novel view depth accuracy DepthAcc (depth accuracy thresholded at 0.1m) for all pixels, agent, and scene, following TotalRecon. Our method outperforms both the multi-video and single-video versions of TotalRecon by a large margin in terms of depth accuracy and LPIPS, due to the ability of leveraging multiple videos. Please see Fig. 7 for the corresponding visual.

Qualitative results of 4D reconstruction can be found in Fig. 5 and the supplementary webpage. A visual comparison with TotalRecon (Single Video) is shown in Fig. 6, where we show that multiple videos helps improving the reconstruction quality on both the agent and the scene.

### 4.2 Interactive Agent Behavior Prediction

**Dataset.** We train agent-specific behavior models for cat, dog, bunny, and human using 4D reconstruction from their corresponding video collections. We use the cat dataset for quantitative evaluation, where the data are split into a training set of 22 videos and a test set of 1 video.

**Implementation Details.** Our model consists of three diffusion models, for goal, path, and full body motion respectively. To train the behavior model, we slice the reconstructed trajectory in the training set into overlapping window of 6.4s, resulting in 12k data samples. We use AdamW to optimize the parameters of the scores functions $\{\theta_\mathbf{Z}, \theta_\mathbf{P}, \theta_\mathbf{G}\}$ and the ego-perception encoders $\{\theta_\psi, \theta_o, \theta_p\}$ for 120k steps with batch size 1024. Training takes 10 hours on a single A100 GPU. Each diffusion model is trained with random dropout of the conditioning (Ho & Salimans, 2022).

**Metrics.** The behavior of an agent can be evaluated along multiple axes, and we focus on goal, path, and body motion prediction. For goal prediction, we use minimum displacement error (minDE) (Chai et al., 2019). The evaluation asks the model to produce $K = 16$ hypotheses, and minDE finds the one closest to the ground-truth to compute the distance. For path and body motion prediction, we use minimum average displacement error (minADE), which are similar to goal prediction, but additionally averages the distance over path and joint angles before taking the min. When evaluating path prediction and body motion prediction, the output is conditioned on the ground-truth goal and path respectively.

**Comparisons and Ablations.** We compare to related methods in our setup and the quantitative results are shown in Tab. 4. To predict the goal of an agent, classic methods build statistical models

Table 5: **Evaluation of Spatial Control.** We evaluate goal-conditioned path generation and path-conditoned full body motion generation respectively.

| Method | Path (m) ↓ | Orientation (rad) ↓ | Joint Angles (rad)↓ |
|---|---|---|---|
| Gaussian (Kendall & Gal, 2017) | $0.206^{\pm 0.002}$ | $0.370^{\pm 0.003}$ | $0.232^{\pm 0.001}$ |
| ATS (Ours) | $\mathbf{0.115}^{\pm 0.006}$ | $\mathbf{0.331}^{\pm 0.004}$ | $\mathbf{0.213}^{\pm 0.001}$ |
| (a) ego→world (Rhinehart & Kitani, 2016) | $0.209^{\pm 0.002}$ | $0.429^{\pm 0.006}$ | $0.250^{\pm 0.002}$ |
| (b) control-unet→code | $0.146^{\pm 0.005}$ | $0.351^{\pm 0.004}$ | $0.220^{\pm 0.001}$ |

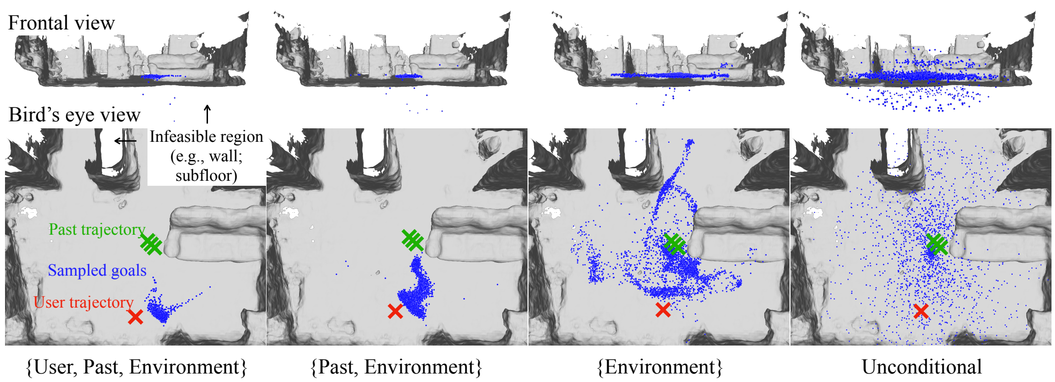



Figure 4: Analysis of conditioning signals. We show results of removing one conditioning signal at a time. Removing observer conditioning and past trajectory conditioning makes the sampled goals more spread out (*e.g.*, regions both in front of the agent and behind the agent); removing the environment conditioning introduces infeasible goals that penetrate the ground and the walls.

of how likely an agent visits a spatial location of the scene, referred to as location prior (Ziebart et al., 2009; Kitani et al., 2012). Given the extracted 3D trajectories of an agent in the egocentric coordinate, we build a 3D preference map over 3D locations as a histogram, which can be turned into probabilities and used to sample goals. Since it does not take into account of the scene and the observer, it fails to accurately predict the goal. We implement a "Gaussian" baseline that represents the goal, path, and full body motion as Gaussians, by predicting both the mean and variance of Gaussian distributions (Kendall & Gal, 2017). It is trained on the same data and takes the same input as ATS. As a result, the "Gaussian" baseline performs worse than ATS since Gaussian cannot represent multi-modal distributions of agent behaviors, resulting in mode averaging. We implement a 1-stage model similar to MDM (Tevet et al., 2022) that directly denoises body motion without predicting goals and paths (Tab. 4 (a)). Our hierarchical model out-performs 1-stage by a large margin. We posit hierarchical model makes it easier to learn individual modules. Finally, learning behavior in the world coordinates (Tab. 4 (b)), akin to ActionMap (Rhinehart & Kitani, 2016), performs worse for all metrics due to the over-fits to specific locations of the scene.

**Analysing Interactions.** We analyse the agent's interactions with the environment and the observer by removing the conditioning signals and study their influence on behavior prediction. In Fig. 4, we show that by gradually removing conditional signals, the generated goal samples become more spread out. In Tab. 4, we drop one of the conditioning signals at a time, and find that dropping either the observer conditioning or the environment conditioning increases behavior prediction errors.

**Spatial Control.** Besides generating behaviors conditioned on agent's perception, we could also condition on user-provided spatial signals (e.g., goal and path) to steer the generated behavior. The results are reported in Tab. 5. We found that ATS performs better than "Gaussians" for behavior control due to its ability to represent complex distributions. Furthermore, egocentric representation produces better behavior generation results. Finally, replacing control-unet architecture by concatenating spatial control with perception codes produces worse alignment (e.g., Path error: 0.115 vs 0.146).

# 5 Conclusion

We have presented a method for learning interactive behavior of agents grounded in 3D environments. Given multiple casually-captured video recordings, we build persistent 4D reconstructions including the agent, the environment, and the observer. Such data collected over a long time period allows us to learn a behavior model of the agent that is reactive to the observer and respects the environment constraints. We validate our design choices on casual video collections, and show better results than prior work for 4D reconstruction and interactive behavior prediction.

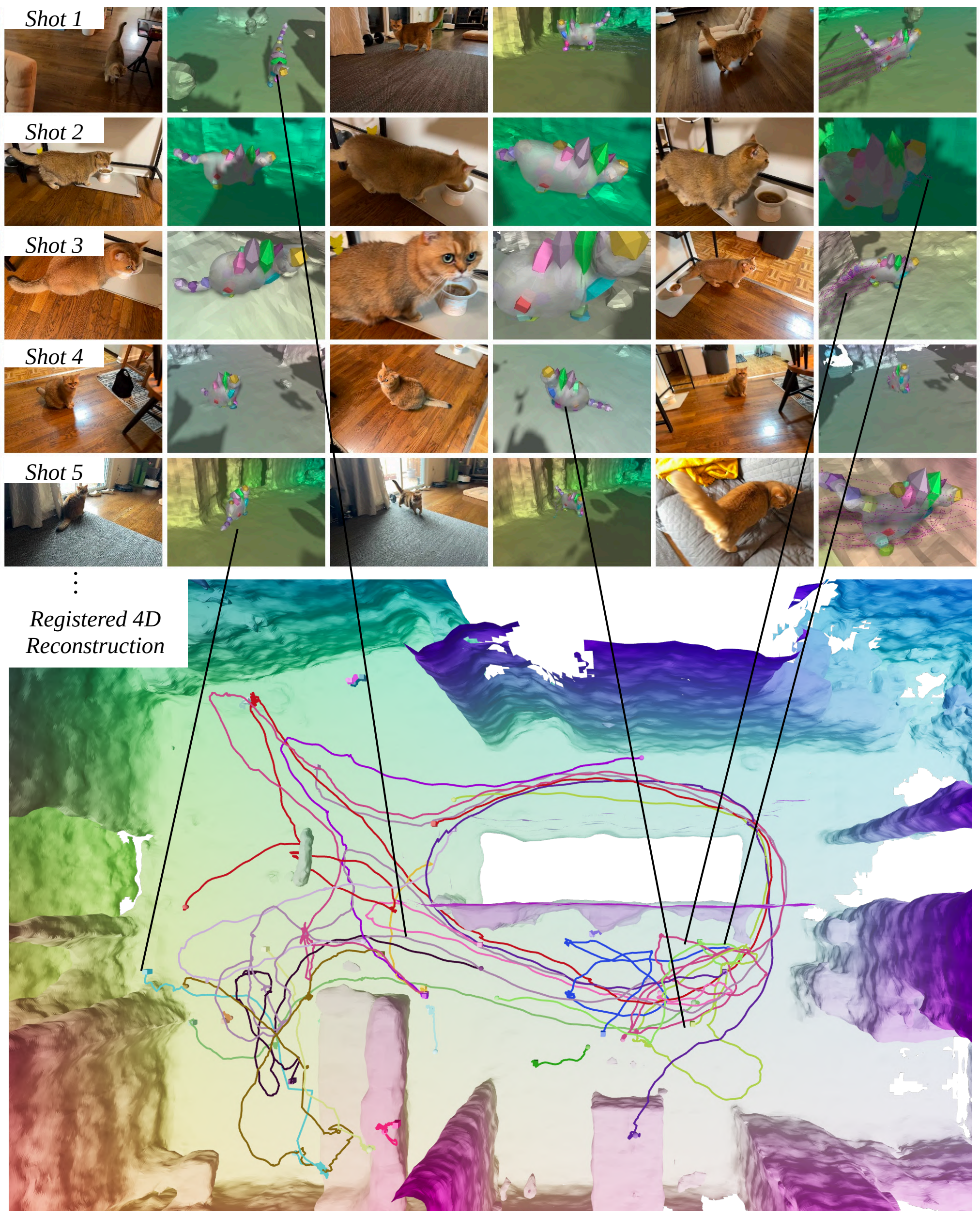



Figure 5: **Results of 4D reconstruction**. Top: reference images and renderings. Background color represents correspondence. Colored blobs on the cat represent $B = 25$ bones (*e.g.*, head is represented by the yellow blob). Bottom: Bird's eye view of the reconstructed scene and agent trajectories, registered to the same scene coordinate. Each colored line represents a unique video sequence where boxes and spheres indicate the starting and the end location.

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Table 6: Table of Notation.

| Symbol | Description |
|---|---|
| | **Global Notations** |
| $B$ | The number of bones of an agent. By defatult $B = 25$. |
| $M$ | The number of videos. |
| $N_i$ | The number of image frames extracted from video $i$. |
| $\mathbf{I}_i$ | The sequence of color images $\{I_1, \ldots, I_{N_i}\}$ extracted from video $i$. |
| $\boldsymbol{\psi}_i$ | The sequence of DINOv2 feature images $\{\boldsymbol{\psi}_1, \ldots, \boldsymbol{\psi}_{N_i}\}$ extracted from video $i$. |
| $T_i$ | The length of video $i$. |
| $T^*$ | The time horizon of behavior diffusion. By default $T^* = 5.6$s. |
| $T'$ | The time horizon of past conditioning. By default $T' = 0.8$s |
| $\mathbf{Z} \in \mathbb{R}^3$ | Goal of the agent, defined as the location at the end of $T^*$. |
| $\mathbf{P} \in \mathbb{R}^{3\times T^*}$ | Path of the agent, defined as the root body trajectory over $T^*$. |
| $\mathbf{G} \in \mathbb{R}^{6B\times T^*}$ | Pose of the agent, defined as the 6DoF rigid motion of bones over $T^*$. |
| $\omega_s \in \mathbb{R}^{64}$ | Scene code, representing the scene perceived by the agent. |
| $\omega_o \in \mathbb{R}^{64}$ | Observer code, representing the observer perceived by the agent. |
| $\omega_p \in \mathbb{R}^{64}$ | Past code, representing the history of events happened to the agent. |
| | **Learnable Parameters of 4D Reconstruction** |
| $\mathbf{T}$ | Canonical NeRFs, including a scene MLP and an agent MLP. |
| $\boldsymbol{\beta}_i \in \mathbb{R}^{128}$ | Per-video code that allows NeRFs to represent variations across videos. |
| $\mathcal{D}$ | Time-varying parameters, including $\{\boldsymbol{\xi}, \mathbf{G}, \mathbf{W}\}$. |
| $\boldsymbol{\xi}_t \in SE(3)$ | The camera pose that transforms the scene to the camera coordinates at t. |
| $\mathbf{G}^0_t \in SE(3)$ | The camera pose that transforms the canonical agent to the camera coordinates at t. |
| $\mathbf{G}^b_t \in SE(3)$ | The transformation that moves bone b from its rest state to time t state. |
| $\mathbf{W} \in \mathbb{R}^B$ | Skinning weights of a point, defined as the probability of belonging to bones. |
| $f_\theta$ | PoseNet that takes a DINOv2 feature image as input and produces camera pose. |
| | **Learnable Parameters of Behavior Generation** |
| $\mathrm{MLP}_{\theta_\mathbf{Z}}$ | Goal MLP that represent the score function of goal distributions. |
| $\mathrm{ControlUNet}_{\theta_\mathbf{P}}$ | Path UNet that represents the score function of path distributions. |
| $\mathrm{ControlUNet}_{\theta_\mathbf{G}}$ | Pose UNet that represents the score function of pose distributions. |
| $\mathrm{ResNet3D}_{\theta_\psi}$ | Scene perception network that produces $\omega_s$ from 3D feature grids $\boldsymbol{\psi}$. |
| $\mathrm{MLP}_{\theta_\mathbf{o}}$ | Observer MLP that produces $\omega_o$ from observer's past trajectory in $T'$. |
| $\mathrm{MLP}_{\theta_\mathbf{p}}$ | Past MLP that produces $\omega_p$ from agent's past trajectory in $T'$. |

# A Appendix

# A Details on Model and Data

**Table of Notation.** A table of notation used in the paper can be found in Tab. 6.

**Summary of I/O.** A summary of inputs and outputs of the method is shown in Tab. 7

**Data Collection.** We collect RGBD videos using an iPhone, similar to TotalRecon (Song et al., 2023). To train the neural localizer, we use Polycam to take the walkthrough video and extract a textured mesh. For behavior capture, we use Record3D App to record videos and extract color images and depth images.

**Diffusion Model Architecture.** The score function of the goal is implemented as 6-layer MLP with hidden size 128. The the score functions of the paths and body motions are implemented as 1D UNets taken from GMD (Karunratanakul et al., 2023). The sampling frequency is set to be 0.1s, resulting a sequence length of 56. The environment encoder is implemented as a 6-layer 3D ConvNet with kernel size 3 and channel dimension 128. The observer encoder and history encoder are implemented as a 3-layer MLP with hidden size 128.

Table 7: Summary of inputs and outputs at different stages of the method.

| Stage | Description |
|---|---|
| Overall | Input: A walk-through video of the scene and videos with agent interactions.<br>Output: An interactive behavior generator of the agent. |
| Localizer Training | Input: 3D reconstruction of the environment and the agent.<br>Output: Neural localizer $f_\theta$. |
| Neural Localization | Input: Neural localizer $f_\theta$ and the agent interaction videos.<br>Output: Camera poses for each video frame. |
| 4D Reconstruction | Input: A collection of videos and their corresponding camera poses.<br>Output: Scene feature volume $\mathbf{\Psi}$, motion of the agent $\mathbf{G}$ and observer $\boldsymbol{\xi}$. |
| Behavior Learning | Input: Scene feature volume $\mathbf{\Psi}$, motion of the agent $\mathbf{G}$ and observer $\boldsymbol{\xi}$.<br>Output: An interactive behavior generator of the agent. |

**Diffusion Model Training and Testing.** We use a linear noise schedule at training time and 50 denoising steps. We train all the diffusion models (goal, path and pose) with classifier-free guidance (Ho & Salimans, 2022; Tevet et al., 2022) that randomly sets conditioning signals to zeros $\mathbf{Z} = \varnothing$ randomly. This allows us to control the trade-off between interactive behavior and unconditional behavior generation, as shown in Fig. 10. At test time, each goal denoising step takes 2ms and each path/body denoising step takes 9ms on an A100 GPU.

## B Additional Results

**Comparison to TotalRecon.** In the main paper, we compare to TotalRecon on scene reconstruction by providing it multiple videos. Here, we include additional comparison in their the original single video setup. We find that TotalRecon fails to build a good agent model, or a complete scene model given limited observations, while our method can leverage multiple videos as inputs to build a better agent and scene model. The results are shown in Fig. 6.

**Visual Ablation on Scene Awareness.** We show final camera and agent registration to the canonical scene in Fig. 9. The registered 3D trajectories provides statistics of agent's and user's preference over the environment.

**Histogram of Agent / Observer Visitation.** We show final camera and agent registration to the canonical scene in Fig. 8. The registered 3D trajectories provides statistics of agent's and user's preference over the environment.

## C Limitations and Future Works

**Environment Reconstruction.** To build a complete reconstruction of the environment, we register multiple videos to a shared canonical space. However, the transient structures (e.g., cushion that can be moved over time) may not be reconstructed well due to lack of observations. We notice displacement of chairs and appearance of new furniture in our capture data. Our method is robust to these in terms of camera localization (Tab. 1 and Fig. 13). However, 3D reconstruction of these transient components is challenging. As shown in Fig 13, our method fails to reconstruct notable layout changes when they are only observed in a few views, e.g., the cushion and the large boxes (left) and the box (right). We leave this as future work. Leveraging generative image prior to in-paint the missing regions is a promising direction to tackle this problem (Wu et al., 2023).

**Scaling-up.** We demonstrate our approach on four types of agents with different morphology living in different environments. For the cat, we use 23 video clips over a span of a month. This isn't large-scale but we believe this is an important step to go beyond a single video. In terms of robustness, we showed a meaningful step towards scaling up 4D reconstruction by neural initialization (Eq. 6).

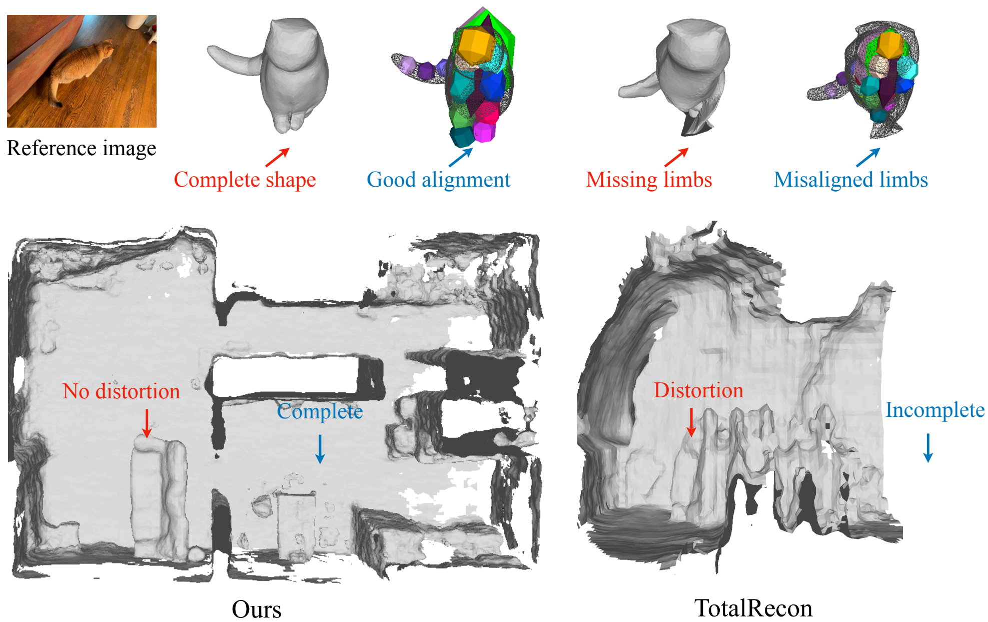



Figure 6: Qualitative comparison with TotalRecon (Song et al., 2023) on 4D reconstruction. Top: reconstruction of the agent at at specific frame. Total-recon produces shapes with missing limbs and bone transformations that are misaligned with the shape, while our method produces complete shapes and good alignment. Bottom: reconstruction of the environment. TotalRecon produces distorted and incomplete geometry (due to lack of observations from a single video), while our method produces an accurate and complete environment reconstruction.

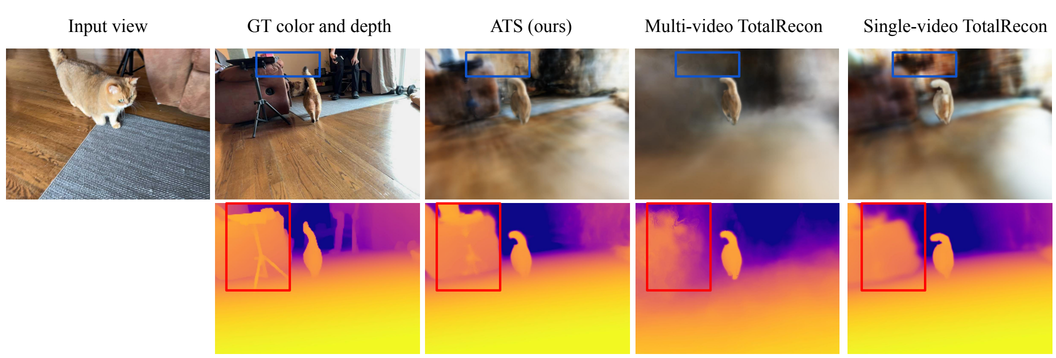



Figure 7: **Qualitative comparison on 4D reconstruction (Tab. 3).** We compare with TotalRecon on 4D reconstruction quality. We show novel views rendered with a held-out camera that looks from the opposite side. ATS is able to leverage multiple videos captured at different times to reconstruct the wall (blue box) and the tripod stand (red box) even they are not visible in the input views. Multi-video TotalRecon produces blurry RGB and depth due to bad camera registration. The original TotalRecon takes a single video as input and therefore fails to reconstruct the regions (the tripod and the wall) that are not visible in the input video.

The major difficulty towards large-scale deployment is the cost and robustness of 4D reconstruction using test-time optimization.

**Multi-agent Interactions.** ATS only handles interactions between the agent and the observer. Interactions with other agents in the scene are out of scope, as it requires data containing more than one agent. Solving re-identification and multi-object tracking in 4D reconstruction will enable introducing multiple agents. We leave learning multi-agent behavior from videos as future work.

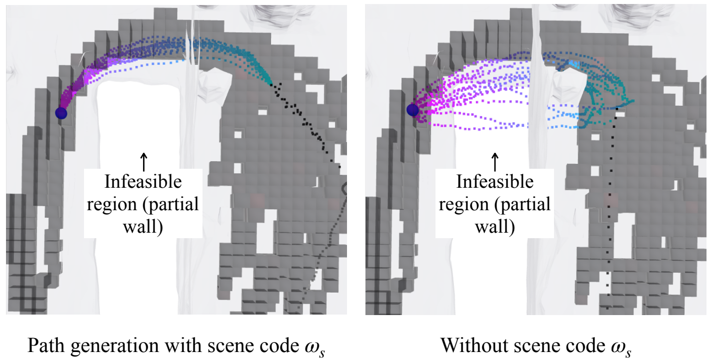



Figure 8: **Visual ablation on scene awareness.** We demonstrate the effect of the scene code $\omega_s$ through goal-conditioned path generation (bird's-eye-view, blue sphere→goal; gradient color→generated path; gray blocks→locations that have been visited in the training data). Conditioned on scene, the generated path abide by the scene geometry, while removing the scene code, the generated paths go through the wall in between two empty spaces.

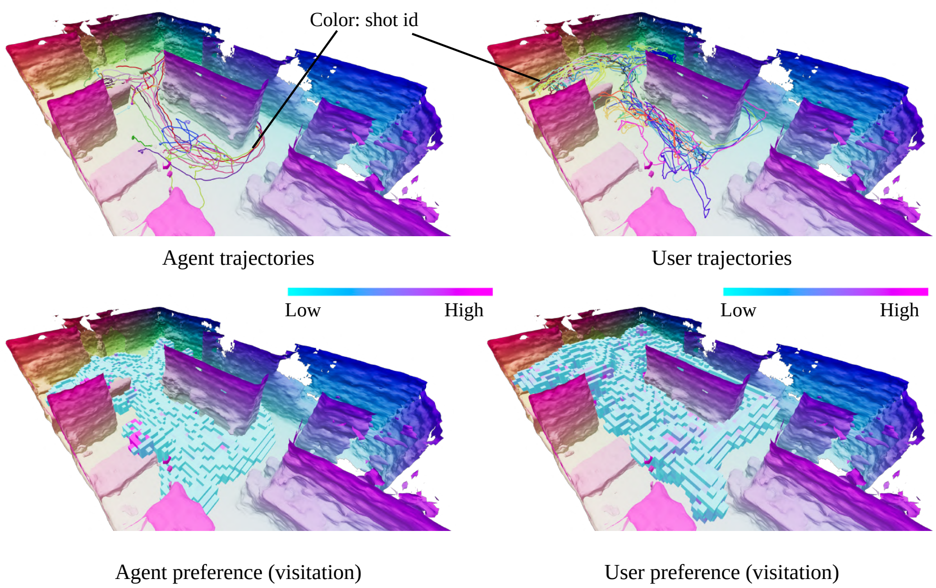
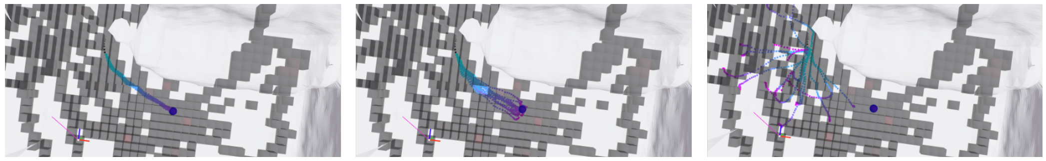



Figure 9: Given the 3D trajectories of the agent and the user accumulated over time (top), one could compute their preference represented by 3D heatmaps (bottom). Note the high agent preference over table and sofa.

**Complex Scene Interactions.** Our approach treat the background as a rigid component without accounting for movable and articulated scene structures, such as doors and drawers. To reconstruct complex interactions with the environment, one approach is to extend the scene representation to be hierarchical (with a kinematic tree), such that it consists of articulated models of interactable objects. To generate plausible interactions between the agent and the scene (e.g., opening a door), one could extend the agent representation $G$ to include both the agent and the articulated objects (e.g., door).

**Physical Interactions.** Our method reconstructs and generates the kinematics of an agent, which may produce physically-implausible results (e.g., penetration with the ground and foot sliding). One



Interactivity (Guidance scale) = 1 Interactivity (Guidance scale) = 0.5 Interactivity (Guidance scale) = 0

Figure 10: **Interactivity of the agent**. By changing the classifier-free guidance scale $s$, we can find a trade-off between interactive behavior and unconditional behavior. We demonstrate the control over interactivity by goal-conditioned path generation (bird's-eye-view, blue sphere$\rightarrow$goal; gradient color$\rightarrow$generated path). With a higher classifier-free guidance scale $s$, the model is controlled more by the conditional generator, and therefore exhibits higher interactivity. $s = 0$ corresponds to fully unconditional generation.

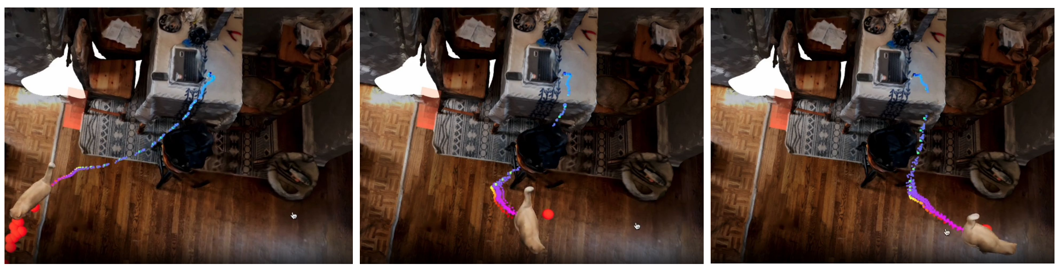


Figure 11: **Generalization ability of the behavior model.** Thanks to the ego-centric encoding design (Eq. 12), a specific behavior can be learned and generalized to novel situations even it was seen once. Although there's only one data point where the cat jumps off the dining table, our method can generate diverse motion of cat jumping off the table while landing at different locations (to the left, middle, and right of the table) as shown in the visual.

promising way to deal with this problem is to add physics constraints to the reconstruction and motion generation (Yuan et al., 2023).

**Long-term Behavior.** The current ATS model is trained with time-horizon of $T^* = 6.4$ seconds. We observe that the model only learns mid-level behaviors of an agent (e.g., trying to move to a destination; staying at a location; walking around). We hope incorporating a memory module and training with longer time horizon will enable learning higher-level behaviors of an agent.

# D SOCIAL IMPACT

Our method is able to learn interactive behavior from videos, which could help build simulators for autonomous driving, gaming, and movie applications. It is also capable of building personalized behavior models from casually collected video data, which can benefit users who do not have access to a motion capture studio. On the negative side, the behavior generation model could be used as "deepfake" and poses threats to user's privacy and social security.

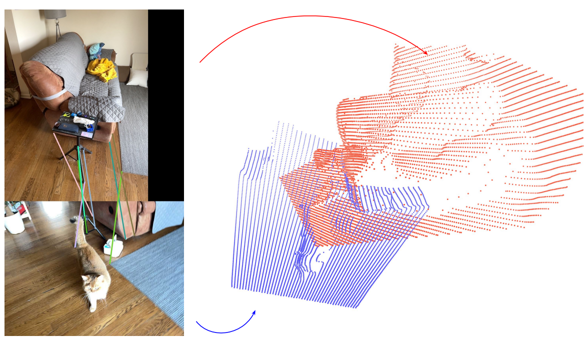


Figure 12: **GT correspondence and 3D alignment.** Left: Annotated 2D correspondence between the canonical scene (top) and the input image (bottom). Right: we visualize the GT camera registration by transforming the input frame 3D points (blue, back-projected from depth) to the canonical frame (red). The points align visually.

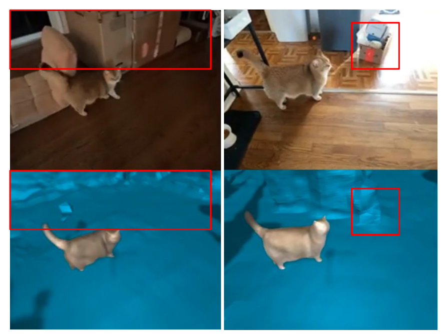


Figure 13: **Robustness to layout changes.** We find our camera localization to be robust to layout changes, e.g., the cushion and the large boxes (left) and the box (right). However, it fails to *reconstruct* layout changes, especially when they are only observed in a few views.