INTERACTION-BASED DISENTANGLEMENT OF ENTITIES FOR OBJECT-CENTRIC WORLD MODELS

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ABSTRACT

Perceiving the world compositionally in terms of space and time is essential to understanding object dynamics and solving downstream tasks. Object-centric learning using generative models has improved its ability to learn distinct representations of individual objects and predict their interactions, and it is a focal question how to utilize the learned representations to solve untrained, downstream tasks. However, as models struggle to predict object interactions and track the objects accurately especially for unseen configurations, using object-centric representations in downstream tasks is yet a challenge. This paper proposes STEDIE, a new model that disentangles object representations based on interactions, into interaction-relevant relational features and interaction-irrelevant global features without supervision. Empirical evaluation shows that the proposed model factorizes global features unaffected by interactions from relational features that are necessary to predict outcome of interactions. We also show that STEDIE, by excluding features irrelevant in predicting interactions, achieves better performance in planning tasks and understanding causal relationships. In both tasks, our model not only achieves better performance in terms of reconstruction ability but also utilizes the disentangled representations to solve the tasks in a structured manner.

1 INTRODUCTION

Humans have evolved to perceive the world in a structured manner, such that we can infer unseen objects, predict their interaction with the environment, and plan to use them to fulfill a certain task. Previous works have emphasized that to achieve similar levels of systematic generalization in deep learning (Goyal & Bengio, 2020), we need a new set of inductive biases that would enable a model to perceive the world as a composition of objects and their relationships (Greff et al., 2020). Recent works on object-centric learning have devised generative models to achieve spatial disentanglement; i.e., these methods decompose images into individual objects in an unsupervised manner (Kosiorek et al., 2018; Greff et al., 2017; Van Steenkiste et al., 2018; Hsieh et al., 2018; Lin et al., 2020; Kossen et al., 2020). This is achieved with the introduction of various inductive biases, examples of which include object propagation and discovery (Kosiorek et al., 2018; Greff et al., 2017; Van Steenkiste et al., 2018), temporal decomposition (Hsieh et al., 2018), background modeling (Lin et al., 2020), and object interaction modeling (Kossen et al., 2020).

Given the success of object-centric learning, several studies have investigated its effectiveness in learning world models (Ha & Schmidhuber, 2018) to solve downstream tasks (Veerapaneni et al., 2020; Watters et al., 2019a; Kossen et al., 2020; Min et al., 2021). As object-centric learning represents the scene as a composition of objects and its interactions, it would drastically reduce the complexity of modeling the temporal evolution of the scene and, therefore, be helpful in predicting the future and planning. For example, Veerapaneni et al. (2020) proposes OP3, the first fully probabilistic object-centric and action-conditioned video prediction model, and shows that it can model interactions between entities and plan to solve simple block stacking tasks. Yet, prior works have still struggled in solving downstream tasks as modeling object interactions accurately and keeping track of objects as individuals are common challenges. Also, not many works have proposed models conditioned on actions (Veerapaneni et al., 2020; Kossen et al., 2020).

To improve the generation quality of videos and downstream performances, we introduce *interaction-based disentanglement*, which aims to factorize the representations of entities into

Table 1: Comparison of relevant prior works on object-centric generative models and its utilization for model-based RL. The models can be categorized based on whether it models interactions, is action-conditioned or not, and type of factorization of object representations. OP3 (Veerapaneni et al., 2020) is similar to our work as it models object interactions and actions by an agent but represents objects as a single latent variable. DDPAE (Hsieh et al., 2018) is also close to our work as it learns factorization implicitly, but interactions are not modeled and is not action-conditioned. For thorough comparison, see Appendix F.

Method	Models interactions	Action-Conditioned (Plannable)	Type of factorization
ViMON	✗	✗	Single
OP3	✓	✓	Single
SQAIR, SCALOR	✗	✗	Explicitly factorized
GSWM	✓	✗	Explicitly factorized
STOVE	✓	✓	Explicitly factorized
DDPAE	✗	✗	Implicitly factorized
STEDIE (ours)	✓	✓	**Implicitly factorized**

interaction-relevant relational features and interaction-irrelevant global features. Here, interaction relevance means that feature would affect the future properties of other objects via interaction; e.g., the weight of objects would be essential to determine whether an object would be moved after contact occurred. At the same time, some objects' features would not be affected via interaction, e.g., the shape of a rigid body would remain unchanged. Importantly, these factorization must be done fully unsupervised to develop a model that can handle various causal relationships, as hand-crafting decomposition for each task is a significant burden and hence infeasible. Table 1 summarizes relevant prior works (Hsieh et al., 2018; Veerapaneni et al., 2020; Kossen et al., 2020). Although learning single representation or explicit factorizing object representations for model-based RL has been introduced in prior works, implicit factorization has not been explored.

To enable interaction-based disentanglement, we propose SpatioTEmporal Disentanglement from Interaction of Entities (STEDIE), a fully-probabilistic, object-centric, and action-conditioned video prediction model. By designing a generative and inference model that implement interaction-based disentanglement, STEDIE disentangles videos both spatially into objects and temporally into relational features and global features. Whereas previous works (Li & Mandt, 2018; Hsieh et al., 2018) have factorized into time-varying and time-invariant features, we model object interactions using neural networks to motivate temporal factorization into *interaction-relevant* and *interaction-irrelevant* features. The model can be trained using only raw input video data in an end-to-end fashion with standard evidence lower bound (ELBO). In our experiments, we first demonstrate the model's ability to disentangle videos spatiotemporally. Furthermore, to verify if decomposing in such way is helpful in solving downstream tasks, we evaluate the trained model on planning task and causal relationship understanding task. In planning task, combined with the cross-entropy method (Rubinstein & Kroese, 2014), we show that STEDIE can perform complex tasks (building block towers) up to 13% better and approximately 2x efficiently than OP3. For causal understanding, we use CausalMBRL (Ke et al., 2021), a recently proposed benchmark of video prediction requiring understanding of causal relationships, we show that it outperforms various baselines, including a standard VAE-based model, object-centric method trained with pixel-based loss function (CSWM (Kipf et al., 2020)), and OP3 by a large margin.

2 Related Works

There have been many researches on using Variational Autoencoders (VAE) (Kingma & Welling., 2013) to learn object-factorized representations for both images and videos with multiple objects. An object-centric generative model trained on videos should learn disentangled representations about not only the objects but also its dynamics, which would lead to better generation of unseen objects or dynamics and understanding of the scenes. Expanding the data domain temporally has been confronted by two major challenges, keeping track of each object and modeling object interactions such as collision. To overcome these hurdles, there has been mainly three approaches in designing

object representations, namely, (1) learning a single representation per object, (2) learning explicit factorization of representation, and (3) learning factorization of representations unsupervised.

First, many researches have used architectures shown to be effective for static images to extract object-level representations from videos (Weis et al., 2020; Veerapaneni et al., 2020; Watters et al., 2019a; Creswell et al., 2020; Min et al., 2021). For example, ViMON (Weis et al., 2020) expands MONet (Burgess et al., 2019) to videos by adding a gated recurrent unit after the encoder to aggregate information over time for each object. OP3 (Veerapaneni et al., 2020) uses IODINE as the inference model with additional modules to capture interactions between objects and action interventions.

Secondly, another branch of researches have derived from AIR (Eslami et al., 2016), a model that learns several predefined factors of objects ("what", "where", and "presence") for a static image, to obtain further disentangled object representations (Kosiorek et al., 2018; Hsieh et al., 2018; Jiang et al., 2019; Kossen et al., 2020; Crawford & Pineau, 2020; Lin et al., 2020). These models, similar to AIR, learn a set of latent variables per object, designed by humans before training, for better object tracking. Introduction of "velocity" and physical interaction (Kossen et al., 2020) or "layer" and background (Jiang et al., 2019; Lin et al., 2020) has improved the model's ability to keep track of objects even in cases when occlusion or interaction occurs.

Thirdly, unsupervised time-wise disentanglement of videos into content and pose of objects has been studied (Li & Mandt, 2018; Hsieh et al., 2018; Zablotskaia et al., 2021; Li et al., 2021). Using VAEs, Hsieh et al. (2018) proposed learning a content vector and a low dimensional vector to predict dynamics for each object in a video, but do not model interactions between objects. Work by Li & Mandt (2018) is closest to ours, in which it proposes a model that learns to disentangle the scene temporally using bi-LSTM (Graves & Schmidhuber, 2005) architecture, but is limited to a single object per scene. Temporal disentanglement into time-varying and time-invariant features has been studied in various domains as well, including texts into topics and details (Bowman et al., 2015), speeches into speaker and linguistic features (Hsu et al., 2017), and images into content and detailed textures (Chen et al., 2016). Unsupervised disentanglement of object representations also relates with how humans recognize the "sameness" of an object (Baillargeon, 1987; Spelke, 1990; Aguiar & Baillargeon, 1999; Spelke et al., 1992; Hespos & Baillargeon, 2001; Spelke & Kinzler, 2007; Spelke, 2013).

Among these three categories, our proposal can be categorized as the third category. Besides, we aim to learn object-centric world models (action-conditioned video prediction models), and to develop the model which can be used on downstream tasks such as multi-step planning. As explained in Table 1, while single representation modeling and explicit factorization modeling methods have been extended for usage in model-based RL (Veerapaneni et al., 2020; Watters et al., 2019a; Kossen et al., 2020; Min et al., 2021), using unsupervised factorization modeling methods have not been explored. In this paper, we reconsider and broaden temporal disentanglement to object interactions as the decomposition into time-invariant, interaction-irrelevant features and time-dependent, interaction-relevant features.

Apart from generative models, models trained using expectation maximization (Greff et al., 2016; 2017; Van Steenkiste et al., 2018), pixel-based losses (Battaglia et al., 2016; Watters et al., 2017; Xu et al., 2019; Piloto et al., 2022), contrastive learning (Kipf et al., 2020) has been proposed. More recently, slot attention (Locatello et al., 2020) has been used to extract object-centric features and predict its dynamics (Kabra et al., 2021; Kipf et al., 2021; Elsayed et al., 2022). For temporal disentanglement, approaches using generative adversarial networks (Goodfellow et al., 2020) and autoencoders have been studied (Tulyakov et al., 2018; Villegas et al., 2017; Denton et al., 2017). As we are interested in learning disentangled representations that can be utilized for downstream tasks, we do not consider competing reconstruction ability with these models as a main objective.

3 Spatiotemporal Disentanglement from Interactions of Entities

Our goal is to build a probabilistic model for a sequence of images, $x^{(0:T)}$ using Markovian latent variables for each timestep, which are further decomposed into object-centric representations for K distinct objects. As we are interested in utilizing the trained model for model-based RL to solve downstream tasks, we assume an invisible agent with a fixed point of view that can interact with the

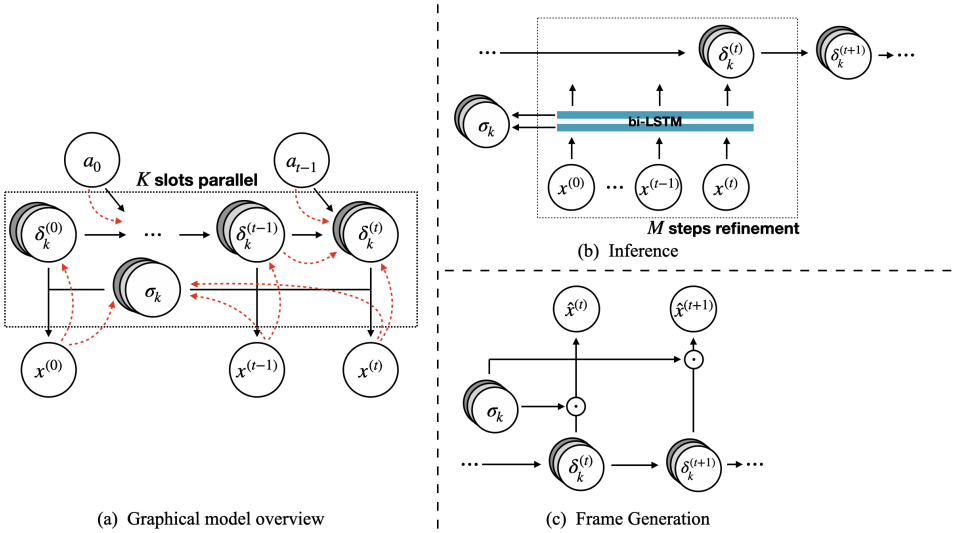

Figure 1: $\sigma_{1:K}$ and $\delta^{(t)}_{1:K}$) denotes global features and relational features respectively. (a) A graphical model visualization of our proposed method, STEDIE. Solid black arrow indicates generation process and dashed red arrow indicates inference procedure. (a) In the inference process, images and actions up to the timestep of interest is used as inputs. (b) To generate at a certain timestep, the relational feature at that timestep is concatenated with the global feature. As two features are inferred independently, the global feature inferred at a previous timestep can be reused.

environment. The actions taken by the agent is expressed as $a^{(0:T-1)}$, which each action consists of moving an object at a certain position to another coordinate. In this paper, we refer the object itself in the real world as *objects* and its latent representations acquired through the model as *entities*.

Figure 1 (a) shows the graphical model of our proposed model, STEDIE. STEDIE learns to disentangle entities into interaction-irrelevant features (*global* features, $\sigma_{1:K}$) and interaction-relevant features (*relational* features, $\delta^{(t)}_{1:K}$). We hypothesize that entities can be factorized based on interactions as object dynamics can be predicted from partial information of the objects. Other features should be learned as they operate as "keys" to identify the same object across time. It is essential to learn model this factorization implicitly to reduce assumption of the data. For example, assuming object size remains unchanged is valid for 2D data but fails for 3D data as objects can move towards or away from the observing agent.

As our model builds and expands OP3 (Veerapaneni et al., 2020), we first explain about OP3 and then proceed to explain the extension we incorporated to learn both global and relational features for each entity.

3.1 Preliminary: Object-centric Perception, Prediction, and Planning (OP3)

OP3, Object-centric Perception, Prediction, and Planning, is a generative model that can decompose videos $x^{(0:T)}$ into K objects $z^{(0:T)}_{1:K}$, predict the effect of actions $a^{(0:T-1)}$ by an agent and object interactions, predict future states, and use obtained representations to solve downstream planning task (Veerapaneni et al., 2020). The model consists of an observation module $p_\theta(x^{(0:T)}|z^{(0:T)}_{1:K})$ and a dynamics module $p_\theta(z^{(t)}_{1:K}|z^{(t-1)}_{1:K}, a^{(t-1)})$, which are trained using variational inference and an inference model $q_\phi(z^{(0:T)}_{1:K}|x^{(0:T)}, a^{(0:T)})$. IODINE (Greff et al., 2019) architecture is used as the inference model. The dynamics module is reused for inference to reduce the number of parameters and training time. For better object-wise decomposition, OP3 proposes interactive inference algorithm which updates both the posterior and the belief over time. OP3 claims interactive inference encourages the model to both disambiguate objects and ensure temporal consistency. Overall, the generative model and inference model can be expressed as $p_\theta(x^{(0:T)}, z^{(0:T)}_{1:K}|a^{(0:T-1)}) = p(z^{(0)}_{1:K}) \prod_{t=1}^{T} p_\theta(z^{(t)}_{1:K}|z^{(t-1)}_{1:K}, a^{(t-1)}) \prod_{t=0}^{T} p(x^{(t)}|z^{(t)}_{1:K})$

and $q_\phi(z_{1:K}^{(0:T)}|x^{(0:T)}, a^{(0:T-1)}) = \prod_{t=0}^{T} q_\phi(z_{1:K}^{(t)}|z_{1:K}^{(t-1)}, x^{(t)}, a^{(t)})$, respectively. Although iterative inference of IODINE and the proposed interactive inference motivates the model to recognize and keep track of objects, experimental results (Appendix D) shows failure cases in which objects move around slots or its color changes over time. We think this is due to dynamics module using full representation of objects; small variances are accumulated over time to cause changes to object features that should remain unaffected by the interactions.

3.2 STEDIE

Generative Model. Figure 1 (c) shows the generation process of our model. STEDIE assumes that an image at timestep t, $x^{(t)}$, is generated from relational features $\delta_{1:K}^{(t)}$ and global features $\sigma_{1:K}$ of K distinct objects. Note that because global features are unaffected by interactions, it remains the same regardless of timestep. Hence, the generative model of observing T frames of scenes $x^{(0:T)}$ and latent entities $\delta_{1:K}^{(0:T)}, \sigma_{1:K}$ from taking actions $a^{(0:T-1)}$ consists of (1) observation module $p_\theta(x^{(t)}|\delta_{1:K}^{(t)}, \sigma_{1:K})$ that renders the image at timestep t conditioned on relational features features $\delta_{1:K}^{(t)}$ and global features $\sigma_{1:K}$ and (2) dynamics moduele $p_\theta(\delta_{1:K}^{(t)}|\delta_{1:K}^{(t-1)}, a^{(t-1)})$ that models object interactions in latent space. Overall, the generative model is expressed as,

$$\begin{aligned} &p_\theta(x^{(0:T)}, \delta_{1:K}^{(0:T)}, \sigma_{1:K}|a^{(0:T-1)}) \\ &= p(\sigma_{1:K}^{(0)}) p_\theta(\delta_{1:K}^{(0)}|\sigma_{1:K}) \prod_{t=1}^{T} p_\theta(\delta_{1:K}^{(t)}|\delta_{1:K}^{(t-1)}, a^{(t-1)}) \prod_{t=0}^{T} p_\theta(x^{(t)}|\delta_{1:K}^{(t)}, \sigma_{1:K}), \end{aligned} \tag{1}$$

where $p(\sigma_{1:K}^{(0)})$ is a Gaussian distribution with mean $\mathbf{0}$ and variance $\boldsymbol{I}$, and $p_\theta(\delta_{1:K}^{(0)}|\sigma_{1:K})$ is modeled with a MLP. We condition relational features on global features as two features are not completely independent. In most cases, static feature affect how the objects move, as the 2D weighted-block pushing dataset (Ke et al., 2021) we use in our experiments is an explicit example.

We model the observation module using a BroadcastCNN (Watters et al., 2019b). Each entity representations $\delta_k^{(t)}, \sigma_k$ is decoded into pixel-wise mean $\boldsymbol{\mu}_k$ and segmentation mask $\boldsymbol{m}_k = p(C = k|\delta_k^{(t)}, \sigma_k)$ to model the likelihood, $p_\theta(x^{(t)}|\delta_{1:K}^{(t)}, \sigma_{1:K}) = \sum_{k=1}^{K} \boldsymbol{m}_k \cdot \mathcal{N}(x^{(t)}; \boldsymbol{\mu}_k, \boldsymbol{\Sigma}^2)$ with the same variance $\boldsymbol{\Sigma}^2$ for all pixels.

Following OP3, we approximate the effect of the intervention on the entities by an action $a^{(t)}$, $p_\theta(\delta_{1:K}^{(t)}|\delta_{1:K}^{(t-1)}, a^{(t-1)})$, by breaking into pairwise interactions. The entire dynamics module is modeled as, using MLP-based function, ℓ, $p_\theta(\delta_k^{(t)}|\delta_k^{(t-1)}, a^{(t-1)}) = \ell(\delta_k^{(t)}|\delta_k^{(t-1)}, a^{(t-1)}, \delta_k^{interact})$ where $\delta_k^{interact} = \sum_{i \neq k}^{K} d_{oo}(\delta_i, \delta_k)$. We apply the same function, d_{oo} for each $k = 1, \cdots, K$ to calculate pairwise entity interactions. While full latent variables were used to predict the dynamics in prior works, our model only takes the relational features, $\delta_{1:K}^{(t)}$. This motivates the model to learn object features unaffected by interactions as global features.

Inference Model and Learning. Figure 1 (b) shows the inference procedure of our model. The inference model is,

$$\begin{aligned} &q_\phi(\delta_{1:K}^{(0:T)}, \sigma_{1:K}|x^{(0:T)}, a^{(0:T)}) \\ &= q_\phi(\sigma_{1:K}|x^{(0:T)}, a^{(0:T-1)}) q_\phi(\delta_{1:K}^{(0)}|x^{(0)}) \prod_{t=1}^{T} q_\phi(\delta_{1:K}^{(t)}|\delta_{1:K}^{(t-1)}, x^{(t)}, a^{(t-1)}), \end{aligned} \tag{2}$$

which is factorized into two parts, (1) inferring the global features from the entire sequence, $x^{(0:T)}, a^{(0:T)}$, and (2) inferring the relational features per timestep. As a single inference to infer the parameters at a certain timestep is insufficient to break the symmetry to decompose a scene into entity representations (Kipf et al., 2020), we incorporate iterative inference in several aspects.

Following OP3, we use iterative inference (Marino et al., 2018) to refine the parameters at each timestep using IODINE (Greff et al., 2019). Iterative inference updates the posterior parameters using gradient information about the ELBO obtained by the current estimate of the parameters. The gradients pass information of what other slots have not learned, therefore encourage slots to capture

different pixels of the image. We also incorporate interactive inference as OP3 and update both the prior and posterior at each timestep. This ensures to keep track of the "same" object using interactive inference for both global and Appendix E).

However, this causes difference in the expressive power of global and relational features as all timesteps up to the current timestep is used to infer global features while relational features is inferred from the current timestep only. Hence, to compensate this problem, we infer global features only at the first refinement step at each timestep. Note that we must infer at the first step as IODINE requires gradients about the ELBO. To infer the global variable, we process the outputs of IODINE through a bi-LSTM network (Graves & Schmidhuber, 2005). To infer object dynamics, we reuse $p_\theta(\delta^{(t)}_{1:K}|\delta^{(t-1)}_{1:K}, a^{(t-1)})$ to reduce the number of parameters and training time (Kossen et al., 2020; Veerapaneni et al., 2020).

As the inference of global and relational features are independent at each timestep, it is also possible to update only either of the features. Inferring features independently allows us to use the model efficiently during test-time; infer both features initially, update only the relational features to predict interactions, then combine the features to reconstruct a scene at any timestep.

Finally, parameters of a generative model p_θ and an inference model q_ϕ is optimized via variational inference to maximize the evidence lower bound (ELBO):

$$\begin{aligned}
&\mathbb{E}_{\delta^{(0:T)}_{1:K},\sigma_{1:K}\sim q_\phi(\delta^{(0:T)}_{1:K},\sigma_{1:K}|x^{(0:T)},a^{(0:T-1)})}\left[\log \frac{p_\theta(x^{(0:T)},\delta^{(0:T)}_{1:K},\sigma_{1:K}|a^{(0:T-1)})}{q_\phi(\delta^{(0:T)}_{1:K},\sigma_{1:K}|x^{(0:T)},a^{(0:T)})}\right] \\
&= \sum_{t=0}^{T}\left(\mathcal{L}_r^{(t)} - \mathcal{L}_c^{(t)}\right) - D_{\mathrm{KL}}(q_\phi(\sigma_{1:K}|x^{(0:T)},a^{(0:T-1)})\|p_\theta(\sigma_{1:K})),
\end{aligned} \tag{3}$$

where $\mathcal{L}_r^{(t)} = \mathbb{E}_{\delta^{(t)}_{1:K},\sigma_{1:K}\sim q_\phi(\delta^{(t)}_{1:K},\sigma_{1:K}|\delta^{(0:t-1)}_{1:K},x^{(0:t)},a^{(0:t-1)})}[\log p_\theta(x^{(t)}|\delta^{(t)}_{1:K},\sigma_{1:K})]$ and $\mathcal{L}_c^{(t)} = D_{\mathrm{KL}}(q_\phi(\delta^{(t)}_{1:K}|\delta^{(t-1)}_{1:K},x^{(t)},a^{(t-1)})\|p_\theta(\delta^{(t)}_{1:K}|\delta^{(t-1)}_{1:K},a^{(t-1)}))$. See appendix for derivation of the loss function (Appendix A) and details on model architecture (Appendix B).

4 Experiments

We evaluate STEDIE using two datasets each with different characteristics: (1) 3D block moving dataset (Blocks) from Janner et al. (2019); Veerapaneni et al. (2020) and (2) 2D weighted-block pushing dataset (Weights) from Ke et al. (2021). Using these datasets, we conduct three experiments aimed to answer the following questions, (1) Have the global and relational features learned different information? and (2) Does modeling to learn disentangled features lead to better performance in downstream tasks, such as planning and causal understanding?

To answer the first question, we conducted latent swapping experiment (subsection 4.1). Specifically, given two unseen samples, we swapped each slot's dynamic feature accordingly and reconstructed the samples. Since all objects are identical except for color, we expect features such as position to be learned as relational features and features such as color to be learned as global features. If the model has learned to disentangle, generating with the swapped relational features will result with sequences with same object colors but different positions.

We then analyzed the impact of learning disentangled representations on two downstream tasks (subsection 4.2). First, we evaluated the learned representations on planning. We used the block stacking task included in Blocks dataset, and use the models to plan the stacking process combined with model-predictive control (MPC) (Finn & Levine, 2017) planning. Intuitively, separating interaction-irrelevant information should help the model plan better because objects follow the same dynamics regardless of objects. Secondly, we use Weights dataset to evaluate whether learning global and relational features contribute to better understanding of underlying causal relationships between objects in a scene. In this experiment, we are interested in investigating whether interaction-based disentanglement is effective for a more complex environment. The trained model should capture object color as interaction-relevant feature to utilize to learn causal structure present in the data.

See appendix for further details on training setup, datasets, and downstream tasks (Appendix C).

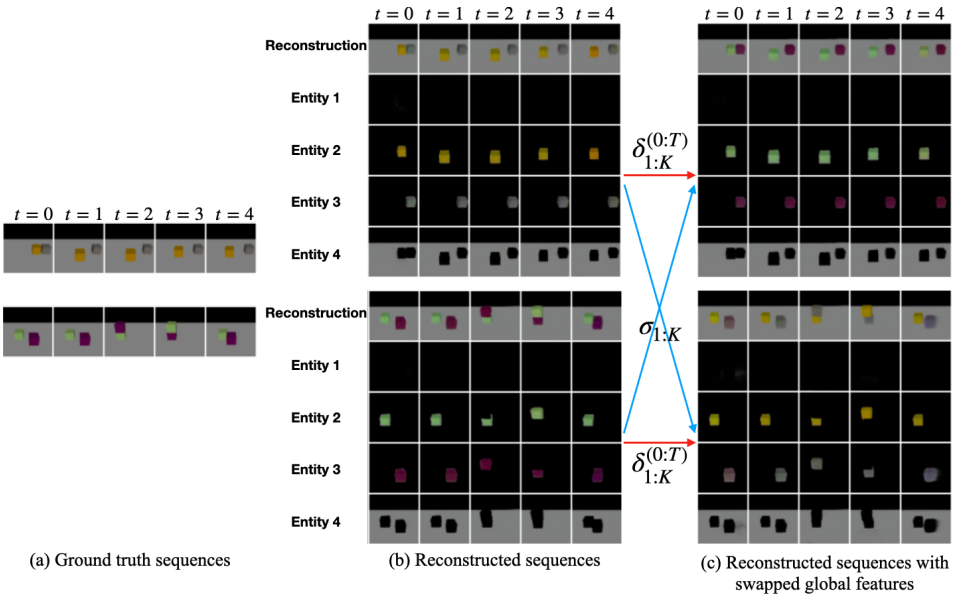

Figure 2: Visualization of swapping global features between two sequences. The columns represent timesteps. The blue arrows indicates that global features were swapped and the red arrows indicates that relational features were kept unswapped. In (b) and (c), the top row is the reconstructed whole image and the second to fifth row are the reconstructed image for each slot. The slots are sorted in ascending order of mask size and global features are swapped between the slots with the same slot #.

Table 2: Color MSE and mask IoU on swapping global or dynamic latent variables between two sequences in the test dataset using STEDIE. Lower MSE indicates color are similar before and after swapping the feature. Higher IoU indicates position are similar.

Swapping feature	MSE (↓)	IoU (↑)
Same global, Different dynamic	**0.0838**	47.4
Same dynamic, Different global	0.1574	**62.8**

4.1 Swapping Latent Variables

Figure 2 visualize an example of generated sequences with originally inferred and swapped global features. By reconstructing the sequence using the swapped global features while retaining the relational features results, the color of the objects are exchanged but their positions remain the same. This suggests that STEDIE successfully disentangled representations into relational features that change through interactions, such as position, and global features that remain unchanged throughout interactions, such as color. We also observed that, due to the disentanglement, STEDIE was able to keep track of objects better even when rolling out longer time-steps (Appendix D).

We further evaluate quantitatively how much object color and position match after swapping the latent variables (Table 2). For slots which object representations are stored in, we calculate mean squared error (MSE) of mean RGB for color difference and intersection over union (IoU) for position difference. We compare the results against the two metrics when swapping the other latent variable. As Table 2 shows, color MSE of original sequence and the sequence with the global variable swapped is lower while having the same dynamic variable leads to better IoU.

Overall, these results show that STEDIE learns to disentangle sequences both spatially into object representations and temporally into time-varying and time-invariant features. The experiment showed that object colors are preserved between sequences with same global variable and object configurations are preserved between sequences with same dynamic variable. Since object representations are learned as two different latent variables, the model is capable of freely combining variables between sequences, suggesting how STEDIE captures the scene in a structured manner.

Table 3: Accuracy (%), MSE, and average CEM steps until reaching goal state of multi-step planning for building block towers by OP3 and our STEDIE model.

# Blocks	Model	Acc. (↑)	MSE (↓)	Average CEM steps (↓)
1	OP3	**85%**	0.0014	1.17
	STEDIE (ours)	84%	**0.0012**	**1.00**
2	OP3	58%	0.0049	1.63
	STEDIE (ours)	**63%**	**0.0041**	**1.45**
3	OP3	42%	0.0102	3.50
	STEDIE (ours)	**55%**	**0.0075**	**1.82**

4.2 Effect on Downstream Tasks

Planning. We compare planning results with OP3 (Veerapaneni et al., 2020). Given representations of current timestep $h^{(t)}_{1:K} = Concat(\sigma_{1:K}, \delta^{(t)}_{1:K})$ and inferred goal representations $h^{g}_{1:K}$, a cost function can be defined as, $\mathcal{C}(h^{(t)}_{1:K}, h^{g}_{1:K}) = \sum_{k \in \mathcal{S}^{(t)}} \min_{l \in \mathcal{S}^{g}} c(h^{(t)}_{k}, h^{g}_{l})$ where $\mathcal{S}^{(t)}$ and $\mathcal{S}^{g}$ denote predicted entities of current timestep and goal image respectively and $c(\cdot)$ is some distance function. Assuming that a single step is enough to move a certain object to its goal position, we can greedily choose the actions that achieve $\min_{k \in \mathcal{S}^{(t)}, l \in \mathcal{S}^{g}} c(h^{(t)}_{k}, h^{g}_{l})$. The actions are sampled and optimized using cross-entropy method (CEM) (Rubinstein & Kroese, 2014).

We evaluate the model using (1) accuracy of $\frac{\text{\# of blocks in the correct position}}{\text{\# goal blocks}}$, where a correct position is based on a threshold of the distance error (Janner et al., 2019), (2) MSE of the reconstructed planned image, and (3) average CEM steps it took when sampling actions. The model was trained using sequences which contain up to two objects.

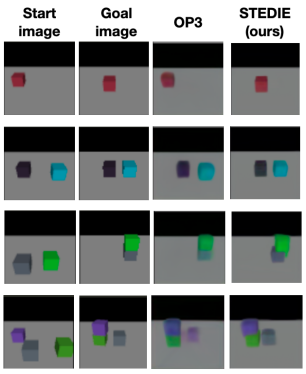

Figure 3: Visualization of start, goal, and reconstruction of reached state by OP3 and STEDIE. STEDIE reach the goal state more accurately.

Figure 3 shows some examples of planning results and Table 3 shows the quantitative results. As the results show, our model exceeds OP3 except for accuracy for when the number of goal blocks is 1. STEDIE achieves higher or equivalent accuracy even for unseen number of objects, which suggests that disentangling interaction-relevant and interaction-irrelevant features reduces redundancy when predicting object dynamics and therefore enabling the model to accurately pick and place the objects. Our model also results in lower reconstruction error, indicating that the model "imagines" more accurately how the objects' layout will change given an action. Lower CEM steps until completion indicates that our model is able to pick the correct actions efficiently. The results especially show improvement in lowering average CEM steps for unseen object configuration (# Blocks=1,3). This supports our hypothesis that separating object representations into global and relational features enhances the model to solve tasks efficiently. By separating irrelevant features, STEDIE is able to find optimal actions efficiently by predicting interactions and tracking objects more accurately.

Understanding Causal Relationship. Table 4 summarizes the reconstruction performance compared to other methods. We compare STEDIE against OP3 as well as two baseline models provided by Kipf et al. (2020) with action vectors incorporated in the dynamics module, using reconstruction MSE as the evaluation metric. For OP3 and STEDIE, the models were trained to predict up to $t = 5$ timesteps. For other baseline models, the same dataset was broken into 5 different single-step rollouts. As the table shows, our method achieves the lowest MSE for most cases, outperforming baseline models which were trained using reconstruction-based loss. This suggests that, compared to other methods, STEDIE understands not only the scenes but has learned the causal relationship between objects, leading to low reconstruction MSE even when rolling out longer into the future.

Figure 4 shows the outcome of a single rollout of each object into all possible directions. The figure shows the ability of STEDIE to understand causal relationships. In this example, the model needs

Table 4: Reconstruction MSE for CausalMBRL dataset calculated at $t = 1, 5, 10$. Except for OP3 and STEDIE, the models were trained in two stages, in which the encoder and the decoder were trained first without transition and the transition module was trained afterwards.

Dataset	Model	Loss	MSE (↓)		
			$(t = 1)$	$(t = 5)$	$(t = 10)$
Observed	VAE	ELBO	167.75	329.83	365.01
	CSWM	Pixel MSE	121.91	282.18	307.91
	OP3	ELBO	160.15	211.79	247.76
	STEDIE (ours)	ELBO	**45.07**	**60.14**	**131.07**
FixedUnobserved	VAE	ELBO	111.37	269.79	310.84
	CSWM	Pixel MSE	95.57	221.61	234.32
	OP3	ELBO	222.34	223.52	223.08
	STEDIE (ours)	ELBO	50.48	**58.78**	**114.31**
Unobserved	VAE	ELBO	110.11	263.43	318.17
	CSWM	Pixel MSE	92.57	215.49	229.85
	OP3	ELBO	218.79	218.99	218.61
	STEDIE (ours)	ELBO	**25.96**	**28.62**	**47.73**

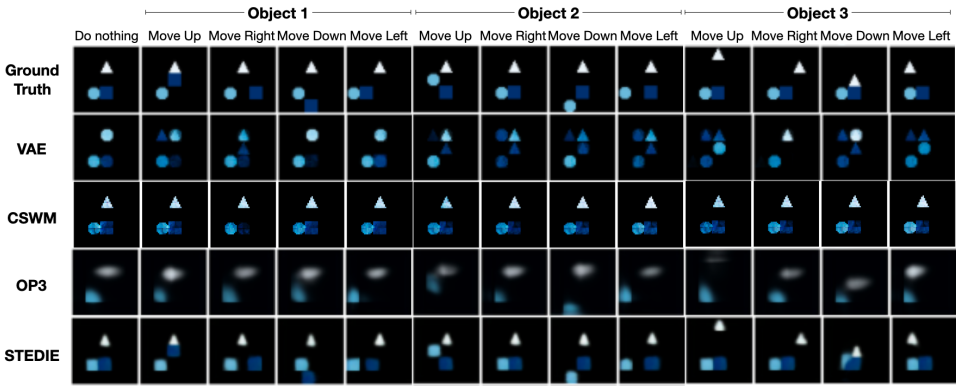

Figure 4: Reconstruction example of every possible single rollout on Weights dataset (Observed). Our model achieves realistic reconstruction for most cases.

to comprehend the relationship for pushing (1) dark blue square (object 1) towards the left or (2) light blue circle (object 2) towards the right. The figure shows that STEDIE is the only model that has captured this causal relationship. However, STEDIE reconstructs the light blue object as square-shaped instead of a circle, suggesting room for further improvement.

5 Conclusion

In this paper, we proposed STEDIE, a model that learns to disentangle an image-action sequence spatially into each objects and temporally into interaction-irrelevant global features and interaction-relevant relational features, trained using only raw input data without any supervision (Equation 3). The first experiment, latent swapping experiment, showed our model's ability to disentangle object representations in a meaningful way. From purely input images and actions, the model decomposed entities into features based on interactions. Based on the next two experiments, it was confirmed that decomposing scenes spatiotemporally leads to better performance in solving downstream tasks. In planning task, separating irrelevant information enabled to model to plan using only positional information to predict interactions. In causal understanding task, the results showed that STEDIE learns the causal relationship between the objects better than other models.

Although we experimented on two datasets with different characteristics, further works on designing a more natural and complex dataset should be considered to explore the effects of learning multiple object features without supervision. We also leave extending this work to other architectures as future work.

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A Derivation of Loss Function

Here we provide derivation of the ELBO. As we define generative model and inference model as Equation 1 and Equation 2 respectively, the ELBO (Equation 3) can be factorized across time,

$$
\begin{aligned}
&\mathbb{E}_{\delta_{1:K}^{(0:T)},\sigma_{1:K}\sim q_\phi(\delta_{1:K}^{(0:T)},\sigma_{1:K}|x^{(0:T)},a^{(0:T-1)})}\left[\log \frac{p_\theta(x^{(0:T)},\delta_{1:K}^{(0:T)},\sigma_{1:K}|a^{(0:T-1)})}{q_\phi(\delta_{1:K}^{(0:T)},\sigma_{1:K}|x^{(0:T)},a^{(0:T)})}\right] \\
&= \mathbb{E}_{\delta_{1:K}^{(0)},\sigma_{1:K}\sim q_\phi(\delta_{1:K}^{(0)},\sigma_{1:K}|x^{(0)})}[\log p_\theta(X^{(0)}|\delta_{1:K}^{(0)},\sigma_{1:K})] - D_{\mathrm{KL}}(q_\phi(\delta_{1:K}^{(0)}|x^{(0)})\|p_\theta(\delta_{1:K}^{(0)}|\sigma_{1:K})) + \cdots \\
&\quad + \mathbb{E}_{\delta_{1:K}^{(t)},\sigma_{1:K}\sim q_\phi(\delta_{1:K}^{(t)},\sigma_{1:K}|\delta_{1:K}^{(0:t-1)},x^{(0:t)},a^{(0:t-1)})}[\log p_\theta(X^{(t)}|\delta_{1:K}^{(t)},\sigma_{1:K})] \\
&\qquad - D_{\mathrm{KL}}(q_\phi(\delta_{1:K}^{(t)}|\delta_{1:K}^{(t-1)},x^{(t)},a^{(t-1)})\|p_\theta(\delta_{1:K}^{(t)}|\delta_{1:K}^{(t-1)},a^{(t-1)})) \\
&\quad - D_{\mathrm{KL}}(q_\phi(\sigma_{1:K}|x^{(0:T)},a^{(0:T-1)})\|p_\theta(\sigma_{1:K})) \\
&= \sum_{t=0}^{T}\left(\mathcal{L}_r^{(t)} - \mathcal{L}_c^{(t)}\right) - D_{\mathrm{KL}}(q_\phi(\sigma_{1:K}|x^{(0:T)},a^{(0:T-1)})\|p_\theta(\sigma_{1:K}))
\end{aligned}
\tag{4}
$$

where

$$
\begin{aligned}
\mathcal{L}_r^{(t)} &= \mathbb{E}_{\delta_{1:K}^{(t)},\sigma_{1:K}\sim q_\phi(\delta_{1:K}^{(t)},\sigma_{1:K}|\delta_{1:K}^{(0:t-1)},x^{(0:t)},a^{(0:t-1)})}[\log p_\theta(x^{(t)}|\delta_{1:K}^{(t)},\sigma_{1:K})] \\
\mathcal{L}_c^{(t)} &= D_{\mathrm{KL}}(q_\phi(\delta_{1:K}^{(t)}|\delta_{1:K}^{(t-1)},x^{(t)},a^{(t-1)})\|p_\theta(\delta_{1:K}^{(t)}|\delta_{1:K}^{(t-1)},a^{(t-1)}))
\end{aligned}
\tag{5}
$$

B Detailed Architecture

We use a similar architecture as OP3 (Veerapaneni et al., 2020) with learning global and relational features for each object as the key difference. In this section, we provide details on the model architecture.

Following IODINE (Greff et al., 2019) and OP3, we use the following inputs to IODINE, where LN means Layernorm and SG means stop gradients. The following image-sized inputs are concatenated and fed to the corresponding convolutional network:

Description	Formula	LN	SG	Ch.
image	$\boldsymbol{x}$			3
means	$\boldsymbol{\mu}$			3
mask	$\boldsymbol{m}_k$			1
mask-logits	$\hat{\boldsymbol{m}}_k$			1
mask posterior	$p(\boldsymbol{m}_k\|\boldsymbol{x},\boldsymbol{\mu})$			1
gradient of means	$\nabla_k\mathcal{L}$	✓	✓	3
gradient of mask	$\nabla\boldsymbol{m}_k\mathcal{L}$	✓	✓	1
pixelwise likelihood	$p(\boldsymbol{x}\|\boldsymbol{h})$	✓	✓	1
leave-one-out likelih.	$p(\boldsymbol{x}\|\boldsymbol{h}_{i\neq k})$	✓	✓	1
coordinate channels				2
			total:	17

We concatenate the posterior parameters $\lambda_{1:K} \in \{\delta_{1:K}, \sigma_{1:K}\}$ and their gradients with the output of the convolutional part of the refinement network and use the result as input to the LSTM network inside IODINE:

Description	Formula	LN	SG
gradient of posterior	$\nabla_{\lambda_k}\mathcal{L}$	✓	✓
posterior	λ_k		

Below, we denote $R_d, d_a, d_\sigma, d_\delta$ as dimensions of deterministic component of latent variable, action vector, global feature, and dynamic feature, respectively. The architecture of the inference model is a combination of IODINE and a bi-LSTM network as follows:

Type	Size/Ch.	Act. Fn.	Comments
MLP	d_δ		for dynamic
MLP	d_σ	Leaky ReLU	for global
biLSTM	$64 + d_a$	Tanh	+actions, for global
MLP	128	Linear	
LSTM	128	Tanh	
Concat $[\lambda_i, \nabla_{\lambda_i}]$	$2R_s$		
MLP	128	ELU	
Avg. Pool	R_s	ELU	
Conv 3×3	R_s	ELU	
Conv 3×3	32	ELU	
Conv 3×3	32	ELU	
Inputs	17		

Latent variables are concatenated along an axis to represent the latent state at a certain timestep. Hence, the architecture of the observation module is as follows:

Decoder

Type	Size/Ch.	Act. Fn.	Comments
Latents	$d_\sigma + d_\delta + R_d$		
Broadcast	$d_\sigma + d_\delta + R_d + 2$		+coordinates
Conv 5×5	32	ELU	
Conv 5×5	32	ELU	
Conv 5×5	32	ELU	
Conv 5×5	32	ELU	
Conv 5×5	4	Linear	RGB+Mask

We follow implementation by OP3 to model object interactions using MLP as follows:

Dynamics Network

Function	Size/Ch.	Act. Fn.
d_o	128	ELU
d_a	32	ELU
$d_{\text{ao-eff}}$	128	ELU
$d_{\text{ao-act}}$	128	Sigmoid
$d_{\text{oo-eff}}$	256	ELU
$d_{\text{ao-act}}$	256	Sigmoid
d_{comb}	256	ELU
f_{det}	128	
f_{sto}	128	

The architecture is a modification of interaction function proposed by Van Steenkiste et al. (2018) by conditioning on actions. Dynamics is composed of effects of the action and effects from other objects, which is modeled as summation of pairwise interactions. Overall, it can be expressed as,

$$\begin{aligned} &\tilde{\delta}_k = d_o(z_k^{(t)}) \qquad \tilde{a} = d_a(a^{(t)}) \qquad \tilde{\delta}_k^{act} = d_{ao}(\tilde{\delta}_k, \tilde{a}) \\ &\delta_k^{interact} = \sum_{i \neq k}^{K} d_{oo}(\tilde{\delta}_i^{act}, \tilde{\delta}_k^{act}) \qquad z_k^{(t+1)} = d_{comb}(\delta_k^{act}, \delta_k^{interact}), \end{aligned} \tag{6}$$

where d_{ao} and d_{oo} are modeled using two neural networks to predict how and to what degree other actions or objects affect an object as, $d_{ao}(\tilde{\delta}_k, \tilde{a}) = d_{\text{ao-eff}}(\tilde{\delta}_k, \tilde{a}) \cdot d_{\text{ao-att}}(\tilde{\delta}_k, \tilde{a})$ and $d_{oo}(\tilde{\delta}_i^{act}, \tilde{\delta}_k^{act}) = d_{\text{oo-eff}}(\tilde{\delta}_i^{act}, \tilde{\delta}_k^{act}) \cdot d_{\text{oo-att}}(\tilde{\delta}_i^{act}, \tilde{\delta}_k^{act})$, respectively. $z_k^{(t)}$ is the concatenation of the deterministic component and stochastic component (relational features). The output $z_k^{(t+1)}$ is split into deterministic component and relational features using separate networks f_{det} and f_{sto} respectively.

C Training and Experiment Setup

For both datasets, we used Adam optimizer and a batch size of 80. We used gradient clipping where if the norm of global gradient exceeds 5.0, then the gradient is scaled down to that norm. As OP3 (Veerapaneni et al., 2020), for better convergence, we divided the latent distribution into a stochastic component (size R_s) and deterministic component (size R_d) which dimensions were both set to 64. Dimensions of global and relational features were both set to 64. We implemented a curriculum training scheme that increases prediction horizon throughout training.

C.1 Blocks Dataset

The 3D block moving dataset, proposed by Janner et al. (2019), is composed from 10000 sequences of moving around two different-colored objects. Each sequence consist of not only images but also action vectors that represent the picking and dropping coordinates. The actions are biased such that 30% of actions will pick up a block and place it at a random position, 40% of actions will pick up a block and place it on top of another block, and 30% of actions are try to pick from a random place and place to another random position. The dataset also has an downstream planning task to evaluate how "good" the representations that the model has learned is. The task consists of a start image (or sequence) and goal image, and we use the model to plan the actions necessary to reach the goal state. The task is split by the number of goal objects $n = [1, 2, 3]$. For a goal with n objects, we plan and execute n steps in total as a single step is sufficient to move the object to its goal configuration. We repeat the planning and executing for $2n$ times or until it has reached the goal state. Accuracy is computed as $\frac{\text{\# of blocks in the correct position}}{\text{\# } goal\ blocks}$, where a correct position is based on a threshold of the distance error.

Training. We trained the model with a fixed learning rate of 0.0005 for 400 epochs. The coefficients of KL divergence terms in the loss function were set to 0.01 for dynamic feature and 0.1 for global feature. Iterative inference was conducted with 4 refinement steps. Number of slots were set to 4.

Planning Task. As the model has learned object-centric representations, it can be used to identify pick location. In order to determine the position of a certain object k, we sample coordinates from a uniform distribution over the (x, y) space and then calculate the weighted average, using its attention coefficient $p(\delta_k|x, y) = \sum_{i \neq k}^{K} d_{\text{oo-att}}(\tilde{\delta}_i^{act}, \tilde{\delta}_k^{act})$ from the dynamics module as its weight. For each action, we sample actions 5 times using CEM method. Given representations of current timestep $h_{1:K}^{(t)} = Concat(\sigma_{1:K}, \delta_{1:K}^{(t)})$ and inferred goal representations $h_{1:K}^{g}$, we use a cost function, $\mathcal{C}(h_{1:K}^{(t)}, h_{1:K}^{g}) = \sum_{k \in \mathcal{S}^{(t)}} \min_{l \in \mathcal{S}^g} c(h_k^{(t)}, h_l^g)$ where $\mathcal{S}^{(t)}$ and $\mathcal{S}^g$ denote predicted entities of current timestep and goal image respectively to calculate how "good" a certain action is. $c(\cdot)$ can be any distance function, but we find that reconstruction MSE results in best performance for both OP3 and STEDIE.

C.2 Weights Dataset

The 2D weighted-block pushing dataset, proposed by Ke et al. (2021), consists of 2D scenes with multiple, different-colored objects. The colors of the objects represent its "weights", such that only a heavier object can move a lighter object while pushing vice versa will result in both objects not moving at all. The dataset consists of three variations, namely, Observed, FixedUnobserved, and Unobserved dataset. In the Observed dataset, all objects have the same shade of color and its intensity represents weight such that darker-colored objects can move lighter objects but not vice versa. In the other datasets, objects' colors are sampled from a discrete colormap. For FixedUnobserved

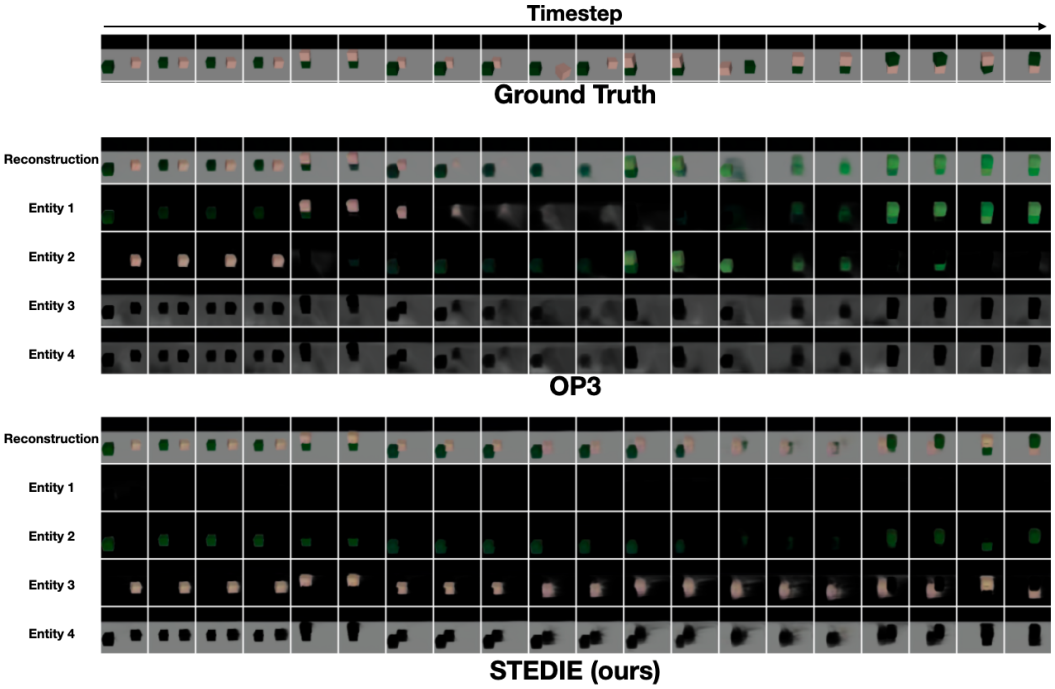

Figure 5: Long-term roll-out results of OP3 and STEDIE. Columns represent timestep. Both models were trained with sequences with a maximum length of 5. Although STEDIE does not reconstruct all timesteps accurately, it is able to track the same object.

dataset, the shapes are coupled with colors and can be interpreted as a hint to identifying its weight. Meanwhile, in the Unobserved dataset, the shapes are distractors and color defines objects' weights.

Training. We trained the model with a fixed learning rate of 0.00067 for 1000 epochs. The coefficients of dynamic feature and global feature's KL divergence terms in the loss function were set 0 initially and linearly increased to 0.01 and 0.1 respectively after 500th epoch in a range of 100 epochs. Iterative inference was conducted with 5 refinement steps. Number of slots were set to 4.

Causal Understanding Task. To evaluate if the trained model has learned causal relationship of objects, we generate a random sequence and visualize the rollout results for all possible actions. At any timestep, the agent may choose to move a certain object one grid horizontally or vertically, or move nothing.

D Rollout Analysis

Although OP3 motivates the model to keep track of objects using interactive inference, we find that it fails to keep track of object features that are temporally invarying (e.g. color). This is because it uses the full representation to predict object interactions; object features that are unaffected by interactions are processed through the neural network, and causes accumulation of small variances. We also find that this causes object to move between slots across time. These problems have a large impact in downstream task performance as the model cannot identify the "same" object between the current timestep and the goal state. Figure 5 shows one example of comparison between OP3 and STEDIE and Figure 6 shows MSE of mean color of slots which include the objects.

We see that STEDIE is more capable of tracking objects better as it learns to disentangle interaction-irrelevant features as global features and use only relational features to predict interactions. On the other hand, we observe that OP3 lacks both spatial and temporal consistency.

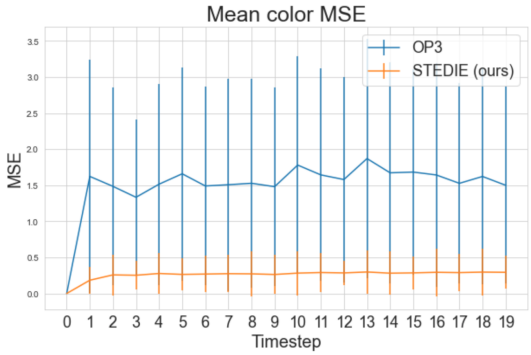

Figure 6: MSE of mean color for slots which include the objects. Mask size of the slots were used to identify whether a slot includes information about an object or not. STEDIE is able to reduce color MSE by a large margin, as it ensures temporal consistency by disentangling based on interactions.

E ABLATIONS

We provide ablation results on interactive inference to infer global features and relational features (Table 5). Following OP3, we update the parameters at each timestep to ensure timewise consistency for both features. Although the model can learn to reconstruct the video without interactive inference, it leads to poor planning performance as object identity is swapped between slots across time.

Table 5: Ablation results on multi-step planning for building block towers on using interactive inference (int. inf.) or not. Evaluation metrics are accuracy (%), MSE, and average CEM steps until reaching goal state. N/A indicates that the model could only predict not to move objects already at its goal position.

# Blocks	STEDIE	Acc. (↑)	MSE (↓)	Average CEM steps (↓)
1	w/ int. inf.	26%	0.0035	1.00
	w/o int. inf.	**84%**	**0.0012**	**1.00**
2	w/ int. inf.	15%	0.0071	1.00
	w/o int. inf.	**63%**	**0.0041**	**1.45**
3	w/ int. inf.	18%	0.0096	N/A
	w/o int. inf.	**55%**	**0.0075**	**1.82**

F COMPARISON WITH OTHER RELATED WORKS

In this section, we provide a more detailed comparison with related works on object-centric learning for multi-object videos (Table 6).

Table 6: Detailed comparison of relevant prior works on object-centric and its utilization for model-based RL. The models can be categorized based on whether it models interactions, is action-conditioned or not, type of factorization of object representations, and objective function.

Method	Models Interactions	Action-Conditioned (Plannable)	Type of factorization	Objective fn.
ViMON	✗	✗	single	ELBO
TBA	✗	✗	single	Pixel-based
DDPAE	✗	✗	implicitly factorized	ELBO
SQAIR, SCALOR	✗	✗	explicitly factorized	ELBO
CSWM, SAVI, SAVI++	✓	✗	single	Pixel-based
OP3	✓	✓	single	ELBO
GSWM	✓	✗	explicitly factorized	ELBO
STOVE	✓	✓	explicitly factorized	ELBO
STEDIE (ours)	✓	✓	implicitly factorized	ELBO