# Object-Centric Representation Learning with Generative Spatial-Temporal Factorization

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## Abstract

Learning object-centric scene representations is essential for attaining structural understanding and abstraction of complex scenes. Yet, as current approaches for unsupervised object-centric representation learning are built upon either a stationary observer assumption or a static scene assumption, they often: i) suffer single-view spatial ambiguities, or ii) infer incorrectly or inaccurately object representations from dynamic scenes. To address this, we propose *Dynamics-aware Multi-Object Network* (DyMON), a method that broadens the scope of multi-view object-centric representation learning to dynamic scenes. We train DyMON on *multi-view-dynamic-scene* data and show that DyMON learns—without supervision—to factorize the entangled effects of observer motions and scene object dynamics from a sequence of observations, and constructs scene object spatial representations suitable for rendering at arbitrary times (*querying across time*) and from arbitrary viewpoints (*querying across space*). We also show that the factorized scene representations (w.r.t. objects) support querying about a single object by space and time independently.

## 1 Introduction

Object-centric representation learning promises improved interpretability, generalization, and data-efficient learning on various downstream tasks like reasoning (e.g. [15, 34]) and planning (e.g. [27, 2, 36]). It aims at discovering compositional structures around objects from the raw sensory input data, i.e. a *binding problem* [9], where the *segregation* (i.e. factorization) introduces the major challenge, especially in cases of no supervision. In the context of visual data, most of the existing focus has been on single-view settings, i.e. decomposing and representing 3D scenes based on a single 2D image [1, 7, 23] or a fixed-view video [20]. These method often suffer from single-view spatial ambiguities and thus show several failures or inaccuracies in representing 3D scene properties. It was demonstrated by Nanbo et al. [28] that such ambiguities could be effectively resolved by multi-view information aggregation. However, current multi-view models are built upon a foundational static-scene assumption. As a result, they: 1) require static-scene data for training and 2) cannot handle well dynamic scenes where the spatial structures evolve over time. These greatly harms a model's potentials in real-world applications.

In this work, we target an unexplored problem—unsupervised object-centric latent representation learning in *multi-view-dynamic-scene* scenarios. Despite the importance of the problem to spatial-temporal understanding of 3D scenes, solving it presents several technical challenges. Consider one particularly interesting scenario where both an observer (e.g. a camera) and the objects in the scene are moving at the same time. To aggregate 3D object information from two consecutive observations, an agent needs not only to handle the cross-view object correspondence problem [28] but also to reason about the independent effects of the scene dynamics and observer motions. One can consider

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the aggregation as a process of answering two questions: "how much has an object really changed in the 3D space" and "what previous spatial unclarity can be clarified by the current view". In this paper, we refer to the relationship between the scene spatial structures and the viewpoints as the *temporal entanglement* because the temporal dependence of them complicates the identification of the *independent generative mechanism* [31].

We introduce DyMON (***Dy**namics-aware **M**ulti-**O**bject **N**etwork*), a unified unsupervised framework for multi-view object-centric representation learning. Instead of making a strong assumption of static scenes as that in previous multi-view methods, we only make two weak assumptions about the training scenes: i) observation sequences are taken at a high frame rate, and ii) there exists a significant difference between the speed of the observer and the objects (see Sec. 3). Under these two assumptions, in a short period, we can transition a *multi-view-dynamic-scene* problem to a *multi-view-static-scene* problem if an observer moves faster than a scene evolves, or to a *single-view-dynamic-scene* problem if a scene evolves faster than an observer moves. These local approximations allow DyMON to learn independently the generative relationships between scenes and observations, and viewpoints and observations during training, which further enable DyMON to address the problem of scene spatial-temporal factorization, i.e. solving the observer-scene *temporal entanglement* and scene object decomposition, at test time.

Through the experiments we demonstrate that: **(i)** DyMON represents the first unsupervised multi-view object-centric representation learning work in the context of dynamic-scene settings that can train and perform object-oriented inference on *multi-view-dynamic-scene* data (see Sec. 5). **ii** DyMON recovers the *independent generative mechanism* of an observer and scene objects from observations and permits querying predictions of scene appearances and segmentations across both space and time (see Sec. 5.1). **(iii)** As DyMON learns scene representations that are factorized in terms of objects, DyMON allows single-object manipulation along both the space (i.e. viewpoint) and time axis—e.g. replays dynamics of a single object without interferring the others (see Sec. 5.1).

## 2 Background

**Object-centric Representations** Consider object-centric representation inference as the inverse problem of an observation generation problem (i.e. the *vision-as-inverse-graphics* [35] idea). In the forward process, i.e. observation generation, we have a scene well-defined by a set of parameter vectors $\mathbf{z} = \{z_k\} = \{z_1, z_2, ..., z_K\}$, where a $z_k \in \mathbb{R}^D$ specifies one and only one object in the scene. An observation of the scene $\mathbf{x}$, e.g. an image $x \in \mathbb{R}^M$ or an RGB image $x \in \mathbb{R}^{M\times 3}$, can be taken only by a specified observer (often defined as $v \in \mathbb{R}^d$) which is independent of the scene in the forward problem, using a specific mapping $g : \mathbb{R}^D \times \mathbb{R}^d \mapsto \mathbb{R}^{M\times 3}$. Assuming a deterministic process, an observation $x$ is generated as $x = g(\mathbf{z}, v)$, where $v$ is often omitted in single-view scenarios (e.g. [1, 7]). With the forward problem defined, we can describe the goal of learning an object-centric representation as inferring the intrinsic parameters of the objects $\{z_k\}$ that compose a scene $\mathbf{z}$ based on the scene observation $\mathbf{x}$. In other words, computing a factorized posterior $p(\mathbf{z}|\mathbf{x}) = p(z_1, z_2, ..., z_K|\mathbf{x})$, even though it is computationally intractable. As the number of objects is unknown in the inverse problem, it is worth noting that i) $K$ is often set globally to be a sufficiently large number (greater than the actual number of objects) to capture all scene objects, and ii) we allow empty "slots".

**Temporal Entanglement** The dynamic nature of the world suggests that the spatial configuration of a scene (denoted by $\mathbf{z}^t$) and an observer $v^t$ are bound to the specific time $t$ that an observation is taken (i.e. $x^t = g(\mathbf{z}^t, v^t)$). Let $\mathbf{X} = \{(x^t, v^t)\}_{1:T}$ [1] represent a data sample, e.g. a sequence or set of multi-view image observations, from dataset $\mathcal{D}$, where $T$ is the number of the images in the sample. Assuming $\mathbf{z}^t$ is given in the data sample for now, i.e. focusing on the generative process only, we augment a scene data sample as $\mathbf{X}_a = \{(x^t, v^t, \mathbf{z}^t)\}_{1:T}$. In general, we assume an independent scene-observer relation: $\mathbf{z}^t \perp v^t|\emptyset$ but they nevertheless become dependent when the corresponding observation is given: $\mathbf{z}^t \not\perp v^t|x^t$. Under a static-scene assumption, we can treat an augmented data sample as $\mathbf{X}_a = \{(x^t, v^t), \mathbf{z}^t\}_{1:T}$ where $\mathbf{z}^t$ and $v^t$ are separable (i.e. can be sampled independently). In this case, to recover the independent generative mechanism (i.e. train a $g(\cdot)$) w.r.t. scenes and observers from data, GQN [6] and MulMON [28] fix $\mathbf{z}^t$ to $\mathbf{z}$ and intervene on the viewpoints $v^t$. From a causal perspective, this can be seen as estimating $p(x^{t'}|\boldsymbol{do}(v^t = v^{t'}), \mathbf{z}^t = \mathbf{z})$,

[1] We define $(\cdot)$ as a joint sample indicator that forbids independent sampling of the random variables wherein.

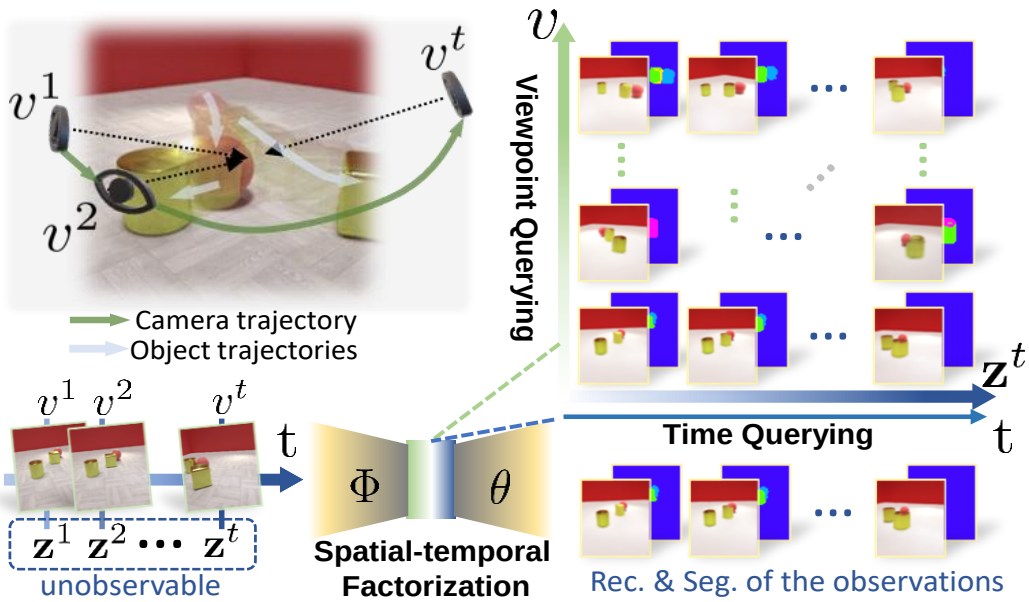


Figure 1: **Top Left:** *Multi-view-dynamic-scene* setup. $v$ with a time index superscript denotes the spatial configuration (e.g. position, orientation, etc.) of an observer at a specific time. We highlight one particular interesting, yet unexplored, scenario where both an observer and scene objects are moving at the same time—which entangles the independent effects of the observer's and scene objects' motions on an scene observation, an image sequence (see **bottom left**). A latent variable $\mathbf{z}$ that is indexed by time describes the spatial of configuration of the scene at a specific time (See Sec. 2 for detailed definition). **Right:** DyMON decouples the generative effects of observer motions and scene object motions and enables: 1) reconstruction and factorization of the observed views (see **bottom right**), and 2) novel-view appearance and decomposition prediction for arbitrary times—querying across both space and time (see **top right**).

where $(x^{t'}, v^{t'}) \sim \{(x^t, v^t)\}_{1:T}$, implicitly under a causal model: $\mathbf{z}^t \rightarrow x^t \leftarrow v^t$. However, in dynamic settings, the same estimation, i.e. sampling $(x^{t'}, v^{t'}) \sim \{(x^t, v^t)\}_{1:T}$ independently of $\mathbf{z}^t$, is forbidden by the $(\cdot)$ indicator. Intuitively, an observer cannot take more than one observations from different viewpoints at the same time $t$. In this paper, we refer to this issue as *temporal entanglement* in view of the temporal implication of the $(\cdot)$ indicator.

# 3 DyMON

Our goal is to train a multi-view object-centric representation learning model that recovers the *independent generative mechanism* of scene object motions and observer motions from dynamic-scene observations. In this section, we detail how DyMON addresses these two presented challenges: 1) temporal disentanglement (see Sec. 3.1), and 2) scene spatial factorization (see Sec. 3.2). We discuss the training of DyMON in Sec. 3.3.

## 3.1 Temporal Disentanglement

The key to resolving *temporal entanglement*, i.e. temporal disentanglement, is to enable sampling $(x^t, v^t)$ independently of $\mathbf{z}^t$, or $(x^t, \mathbf{z}^t)$ independently of $v^t$. This is seemingly impossible in the *multi-view-dynamic-scene* setting as it requires to fix either $\mathbf{z}^t$ (static scene) or $v^t$ (single-view) respectively. In this paper, we make two assumptions about the training scenes to ensure the satisfaction of the aforementioned two requirements without violating the global *multi-view-dynamic-scene* setting. Let us first describe the dynamics of scenes and observers with two independent dynamical systems:

$$\mathbf{z}^{t+\Delta t} - \mathbf{z}^t = \overline{f_{\mathbf{z}}}(\mathbf{z}^t, t)\Delta t \quad , \quad v^{t+\Delta t} - v^t = \overline{f_v}(v^t, t)\Delta t, \tag{1}$$

where $t$ and $t + \Delta t$ are the times that two consecutive observations were taken, $\overline{f_{\mathbf{z}}}(\mathbf{z}^t, t)$ and $\overline{f_v}(v^t, t)$, or simply $\overline{f_{\mathbf{z}^t}}$ and $\overline{f_{v^t}}$, are the average velocities of scene objects and the observer within $[t, t + \Delta t]$.

With the dynamical systems defined, we introduce our assumptions (which define a tractable subset of all possible situations) as:

- **(A1)** ***The high-frame-rate assumption*** $\Delta t \to 0$ s.t. $x^{t+\Delta t} \approx x^t$,
- **(A2)** ***The large-speed-difference assumption*** The data comes from one of two cases (SCFO: Slow Camera, Fast Objects or FCSO: Fast Camera Slow Objects), that satisfy: $|\frac{|\overline{f_{\mathbf{z}}}|}{|\overline{f_v}|}| \geq C_{SCFO}$ or $|\frac{|\overline{f_{\mathbf{z}}}|}{|\overline{f_v}|}| \leq C_{FCSO}$, where $|velocity|$ computes a speed, and $C_{SCFO}$ and $C_{FCSO}$ are positive constants.

**A1** allows us to assume a nearly static scene $\mathbf{z}^t$ or a fixed viewpoint $v^t$ for a short period. Consider an example where we assume a static scene, i.e. $\mathbf{z}^{\tau-\Delta t} \approx \mathbf{z}^{\tau} \approx \mathbf{z}^{\tau+\Delta t}$, in $[\tau - \Delta t, \tau + \Delta t]$, **A1** essentially allows us to extract $\mathbf{z}^t$ out of a joint sample as: $\mathbf{X}_a = \{(x^t, v^t), \mathbf{z}^t\}_{\tau-\Delta t:\tau+\Delta t}$. An intuitive way to define **A2** is: $|\overline{f_{\mathbf{z}}}| \gg |\overline{f_v}|$ or $|\overline{f_{\mathbf{z}}}| \ll |\overline{f_v}|$, which specify a large speed difference between scene speeds and observer speeds.

These two assumptions enable us to accumulate instant changes (velocities) on one variable (e.g. either $\mathbf{z}^t$ or $v^t$) over a finite number of $\Delta t$ while ignoring the small changes of the other (assumed fixed). We then treat a *slow-camera-fast-objects* (i.e. SCFO) scenario, where $|\overline{f_{\mathbf{z}}}| \gg |\overline{f_v}|$, as an approximate *single-view-dynamic-scene* scenario, and a *fast-camera-slow-objects* (i.e. FCSO) scenario, where $|\overline{f_{\mathbf{z}}}| \ll |\overline{f_v}|$, an approximate *multi-view-static-scene* scenario. Either case allows us to resolve the *temporal entanglement* problem. Importantly, to answer the question: "is a given data sample an SCFO or FCSO sample", we need to quantitatively specify the two assignment criteria $C_{SCFO}$ and $C_{FCSO}$. However, a direct calculation of these two constants is often difficult and does not generalize as: i) $|\overline{f_{\mathbf{z}}}|$ is not available in unsupervised scene representation learning data, and ii) the two constants vary across different datasets. In practice, we cluster the data samples into SCFO and FCSO clusters using only the viewpoint speed $|\overline{f_v}|$, i.e. assuming $|\overline{f_{\mathbf{z}}}| = 1$ for training (see Sec. 3.3). In testing, DyMON treats them equally.

### 3.2 Spatial Object Factorization

DyMON tackles scene spatial decomposition in a similar way to MulMON [28] using a generative model and an inference model. The generative likelihood of a single image observation is modelled with a spatial Gaussian mixture [33, 8]:

$$p_\theta(x^t|\mathbf{z}^t = \{z_k^t\}, v^t) = \prod_{i=1}^{M} \sum_{k=1}^{K} p_\theta(C_i^t = k|z_k^t) \cdot \mathcal{N}(g_\theta(z_k^t, v^t), \sigma^2\mathbf{I}), \tag{2}$$

where $i$ indexes a pixel location ($M$ in total) and RGB values that pertain to an object $k$ are sampled from a Gaussian distribution $\mathcal{N}(g_\theta(z_k^t, v^t), \sigma^2\mathbf{I})$ whose mean is determined by the decoder network $g_\theta(\cdot)$ (defined in Sec. 2) with trainable parameter $\theta$ and standard deviation $\sigma$ is globally set to a fixed value $0.1$ for all pixels. The mixing coefficients $p_\theta(C_i = k|z_k)$ capture the categorical probability of assigning a pixel $i$ to an object $k$ (i.e. $C_i = k$). This imposes a competition over the $K$ objects as every pixel has to be explained by one and only one object in the scene.

DyMON adapts the *cross-view inference module* [28] of MulMON to handle: i) the cross-view object correspondence problem, ii) recursive approximation of a factorized posterior, and iii) temporal evolution of spatial structures (which indicates the major difference between the inference modules of DyMON and MulMON). The decomposition and recursive approximation of the posterior is:

$$p(\mathbf{z}^t = \{z_k^t\}|x^{\leqslant t}, v^{\leqslant t}) \approx q_\Phi(\mathbf{z}^t = \{z_k^t\}|x^{\leqslant t}, v^{\leqslant t}) = q(\mathbf{z}^0) \prod_t q_\Phi(\mathbf{z}^t|x^t, v^t, \mathbf{z}^{<t}), \tag{3}$$

where $q_\Phi(\mathbf{z}^t|x^t, v^t, \mathbf{z}^{<t})$ denotes the approximate posterior to a subproblem w.r.t. an observation $x^t$ taken from viewpoint $v^t$ at time $t$, and assumes a standard Gaussian $\mathcal{N}(\mathbf{0}, \mathbf{I})$ for the scene prior $q(\mathbf{z}^0)$. The intuition is to treat a posterior inferred from previous observations as the new prior to perform Bayesian inference for a new posterior based on a new observation. We use $\mathbf{z}^t$ to denote the inferred scene representations after observing $x^t$, i.e. a new posterior, and $\mathbf{z}^{<t}$ to denote the new prior before observing $x^t$. Note that we can advance $t$ either regularly or irregularly. The single-veiw (or within-view) inference is handled by DyMON using *iterative amortized inference* [24] with amortization function $\Phi$ (modelled with neural networks). Refer to Appendix B. for full details about the generative and inference models of DyMON.

### 3.3 Training

**Algorithm 1: DyMON Training Algorithm**

**Input:** training data $\mathcal{D}$
**Hyperparameters** $|\mathcal{Q}|$, $(\beta_{FCSO}, \beta_{SCFO})$, $(\Delta t, \Delta\tau)$ ; // $\Delta t > \Delta\tau > 2, |\mathcal{Q}| = \textbf{sizeof}(\mathcal{Q})$
**Initialize** *trained parameters* $\Phi$, $\theta$, *and latent prior* $\boldsymbol{\lambda}^0 = \{(\mu_k = \mathbf{0}, \sigma_k = \mathbf{I})\}$;
**repeat**
  **Sample** *a sequence* $\mathbf{X} = \{(x^t, v^t)\}_{1:T} \sim \mathcal{D}$ ; // $T$ (RGB images, viewpoints)
  **if** $\textbf{assign}(\mathbf{X}; \mathcal{D}) == FCSO$ **then**
    $\beta$, $\Delta t_v$, $\Delta t_{\mathbf{z}} = \beta_{FCSO}$, $\Delta\tau$, $\Delta t$ ; // $\Delta t_v < \Delta t_{\mathbf{z}}$, update $v^t$ more often
  **else**
    $\beta$, $\Delta t_v$, $\Delta t_{\mathbf{z}} = \beta_{SCFO}$, $\Delta t$, $\Delta\tau$ ; // $\Delta t_{\mathbf{z}} < \Delta t_v$, update $\mathbf{z}^t$ more often
  $\mathcal{T} = \textbf{random_walk_t}(\text{s} = 1, \text{e} = T, \text{step_dist} = \mathcal{U}\{\Delta t_{\mathbf{z}} - 2, \Delta t_{\mathbf{z}} + 2\})$ ;
  $(x, v)$, $t$, $\boldsymbol{\lambda}^t$, $\boldsymbol{ELBO}$, $\boldsymbol{LL}_{query}$, $= \mathbf{X}[1]$, $1$, $\boldsymbol{\lambda}^0$, $0$, $0$;
  **while** $t \leqslant T$ **do**
    $(x^t, v^t) = \mathbf{X}[t]$ ;
    **if** $\textbf{mod}(t, \Delta t_v) == 0$ **then**
      $v = v^t$ ; // update $v$
    **if** $t \in \mathcal{T}$ **then**
      $x = x^t$ ; // update $x$
      $\boldsymbol{ELBO}^{(t)}$, $\boldsymbol{\lambda}^t = \textbf{iterative_inference}_{\Phi,\theta}(x, v, \boldsymbol{\lambda}^t)$ ;
      $\mathbf{z^t} \sim \mathcal{N}(\mathbf{z}^t; \boldsymbol{\lambda}^t)$ ; // sample updated $\mathbf{z}^t$
      $\mathcal{Q} = \{t_q\} = \textbf{sample_query_t}(\text{dist} = \mathcal{U}\{t - \Delta t_{\mathbf{z}}/2, t + \Delta t_{\mathbf{z}}/2\}, \text{size} = |\mathcal{Q}|)$;
      **for** $t_q \in \mathcal{Q}$ **do**
        $(x^q, v^q) = \mathbf{X}[t_q]$;
        $\boldsymbol{LL}_{query} += (1/(|\mathcal{Q}| \cdot |\mathcal{T}|)) \cdot \log p_\theta(x^q | \mathbf{z}^t, v^q)$ ; // fix $\mathbf{z}^t$, **do** $v = v^q$
      $\boldsymbol{ELBO} += (1/|\mathcal{T}|) \cdot \boldsymbol{ELBO}^{(t)}$;
    $t += 1$;
  $\mathcal{L} = \boldsymbol{ELBO} + \beta \cdot \boldsymbol{LL}_{query}$ ; // $\beta_{FCSO} > \beta_{SCFO}$
  $\theta$, $\Phi \leftarrow \textbf{optimizer}_{\textbf{max}}(\mathcal{L}, \theta, \Phi)$;
**until** $\theta, \Phi$ *converge*;

Similar to MulMON [28], we train DyMON by maximizing the following objective function that linearly combines an evidence lower bound (abbr. ELBO) and the log likelihood (abbr. LL) of the querying views:

$$\begin{aligned}\mathcal{L} =& \boldsymbol{ELBO} \; + \; \beta \cdot \boldsymbol{LL}_{query} \\ =& \frac{1}{|\mathcal{T}|} \sum_{t \in \mathcal{T}} \mathbf{E}_{q_\Phi(\mathbf{z}^t|\cdot)}[\log p_\theta(x^t|\mathbf{z}^t, v^t)] - \frac{1}{|\mathcal{T}|} \sum_{t \in \mathcal{T}} \mathcal{D}_{\mathrm{KL}}[q_\Phi(\mathbf{z}^t|x^{\leqslant t}, v^{\leqslant t}) || q_\Phi(\mathbf{z}^{<t}|x^{<t}, v^{<t})] \\ &+ \beta \cdot \frac{1}{|\mathcal{T}| \cdot |\mathcal{Q}|} \sum_{q \in \mathcal{Q}} \mathbf{E}_{q_\Phi(\mathbf{z}^t|\cdot)}[\log p_\theta(x^q|\mathbf{z}^t, v^q)],\end{aligned} \tag{4}$$

where $\mathcal{T}$ and $\mathcal{Q}$ record the times when DyMON performs inference and $v^t$ interventions (i.e. viewpoint-queried generation) and $\beta$ is the weighting coefficient. We construct $\mathcal{T}$ by sampling $t$ (either regularly or irregularly) with a random walk through $[1, T]$, where a uniform distribution $\mathcal{U}\{\Delta t - 2, \Delta t + 2\}$ of an expected value $\Delta t$ ($> 2$) is used as the step distribution. As shown in Algo. 1, by varying the updating periods of $\mathbf{z}^t$ and $v^t$ (denoted as $\Delta t_{\mathbf{z}}$ and $\Delta t_v$ respectively), we have DyMON imitates the behaviours of a *multi-view-static-scene* model and a *single-view-dynamic-scene* model to handle the SCFO and FCSO samples respectively. In addition, using different $\beta$ for the SCFO and FCSO samples allows alternating the training focus between spatial reasoning (w.r.t. objects and viewpoints) and temporal updating.

**Assignment Function and Batching** To behave according to different types of data, we need to determine if a $\mathbf{X} \sim \mathcal{D}$ is, for example, an SCFO sample or not. Under **A2**, we consider any dataset

consisting of only a mix of SCFO and FCSO samples (where a sample is a sequence of images). For a given dataset, we cluster all training samples of a dataset into two clusters w.r.t. the SCFO and FCSO scenarios. This then gives us an assignment function, $\mathbf{assign}(\mathbf{X}; \mathcal{D})$ (as shown in Algo. 1. In practice, to avoid breaking parallel training processes with loading SCFO and FCSO samples into the same batch, we assign the training data beforehand instead of assigning every data sample on the fly during training. This allows to batch FCSO or SCFO samples independently at every training step.

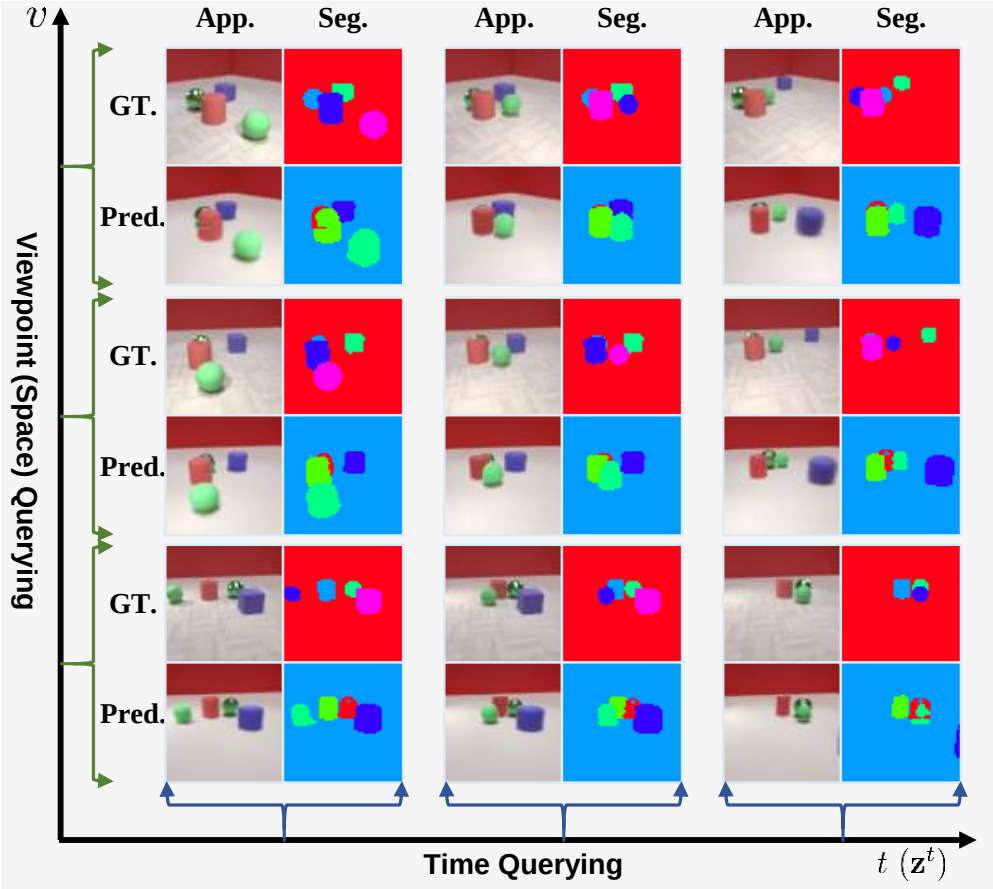


Figure 2: Qualitative results of spatial-temporal factorization. The GT rows show the true scene. The Pred entries are the corresponding scene re-rendered from the model. The vertical row pairs show the results from viewpoint changes and the horizontal direction shows the results at different times.

## 4 Related Work

**Single-View-Static-Scene** The breakthrough of unsupervised object discovery based on a primary scenario, i.e. a single-view-image setting, lays a solid foundation for the recent rise of unsupervised object-centric representation learning research. Built upon a VAE [18], early success was shown by AIR [5] that searches one object at a time on image regions. Because AIR and its successors (e.g. [19]) treat objects as flat pixel patches and the image generation process as "paste flat objects on canvas" using a spatial transformer [14], they are unable to capture 3D spatial properties. To overcome this, most recent advances [1, 7, 21, 4, 23, 3] model a single 2D image with a spatial Gaussian mixture model [33, 8] that allows explicit handling of background and occlusions. Although these models suffer from single-view ambiguities like occlusions or optical illusions, they have the potential for attaining factorized representations of 3D scenes. Our work has close relationship to IODINE [7]: we handle the object-wise inference from an image observation at each time point using the *iterative amortized inference* [24] design and capture the compositional generative process with a spatial Gaussian mixture model.

**Multi-View-Static-Scene** A natural way of resolving single-view ambiguities is to aggregate information from multi-view observations. Although multi-view exploration of a scene does not directly

facilitate object-level factorization of 3D scenes, Eslami et al. [6] demonstrated that it does reduce the spatial uncertainty and enable explicit 3D knowledge evaluation—novel-view prediction. To attain object-centric decomposition of 3D scenes, Nanbo et al. [28] introduced MulMON as a combination of GQN [6] and IODINE [7]. Despite MulMON's ability to leverage multi-view exploration to extract accurate object representations of 3D scenes, like GQN, MulMON can only train on static-scene samples and thus does not generalize well to dynamic scenes. In this work, we propose DyMON as an extension of MulMON to dynamic scenes. Also, one can see DyMON as a unified model for unsupervised multi-view object-centric representation learning.

**Single-View-Dynamic-Scene** A line of unsupervised scene object-centric representation learning research was established on the *single-view-dynamic-scene* setting [11, 19, 16], where they explicitly model and represent object dynamics based on video observations. However, as most of these works employ a similar image composition design to AIR, they deal with only flat 2D objects that are similar to MNIST digits and thus cannot model 3D spatial properties. The most closely related work is that of Lin et al. [20] where they modelled relative depth information and pair-wise interactions of 3D object patches. In our work, the spatial-temporal factorization allows us to show the dynamics and depths of the objects from different viewpoints at different times.

**Other Related Work** Our work is related to disentangled representation learning research. Traditional disentanglement learning works aims to achieve a feature-level disentanglement [10, 17, 22] aka. an intra-object disentanglement. Correspondingly, object-centric representation learning, i.e. spatial factorization, targets an inter-object disentanglement. In addition to an object-level factorization, we also factorize the time-dependent scene-observer entanglement that is introduced by the *multi-view-dynamic-scenes*. Disentanglement problems are often formulated under the frameworks of causal inference [29, 32, 31] and *independent component analysis* (abbr. ICA) [13, 12]. In this work, we make two key assumptions that allow us to identify the *independent generative mechanism* and facilitate disentangled representation learning [31]. Recent trend of neural radiance field (e.g. [26, 25, 30]) are relevant to our work in the sense of attaining 3D-scene representations using multi-view observations. These methods only aim to memorize the volumetric structure of a single scene during "training" and then use its memory to perform novel-view synthesis. Therefore, from an *vision-as-inverse-graphics* [35] perspective, we do not consider these models scene understanding models as they are unable to infer the representations of unseen scenes.

# 5 Experiments

We used two simulated *multi-view-dynamic-scene* synthetic datasets, namely DRoom and MJC-Arm, and we conducted quantitative analysis on DRoom and show qualitative results on the other two datasets. The DRoom dataset consists of five subsets (including both training and testing sets): one subset (denoted as DR0-$|\overline{f_{\mathbf{z}}}|$) with zero object motion (*multi-view-static-scene* data), one subset (denoted as DR0-$|\overline{f_v}|$) with zero camera motion (*single-view-dynamic-scene* data), and three *multi-view-dynamic-scene* subsets of increasing speed difference levels from 1 to 3 (denoted as DR-Lvl.1 $\sim$ 3). Each of the six subsets consists of around $200$ training sequences ($40$ frames of RGB images per sequence) and $20$ testing sequences ($40$ frames from $12$ different views, i.e. $57.6k$ images). Although DyMON's focus is on a more general problem, we nevertheless compare it against two recent and specialized unsupervised object-centric representation learning methods, i.e. GSWM [20], and MulMON [28], in two respective settings: *single-view-dynamic-scenes*, and *multi-view-static-scenes*. All models were trained with 3 different random seeds for quantitative comparisons. Refer to our supplementary material for full details on experimental setups, and ablation studies and more qualitative results.

## 5.1 Space-Time Querying

The recovery of *the independent generative mechanism* permits DyMON to make both viewpoint-queried and time-queried predictions, i.e. querying across space and times, of scene appearances and segmentations using the inferred scene representations, which enables the below two demonstrations:

**Novel-view Prediction at Arbitrary Times** Recall that a scene observation $x$ is the generative product of a specific scene (composed by objects) and observer at a specific time $t$ with a well-defined generative mapping, i.e. $x = g(\mathbf{z}, v)$ (see sec. 2). Like previous multi-view object-centric representation learning models (e.g. MulMON [28]), we query from an arbitrary viewpoint $v$ w.r.t.

a scene of interests $\mathbf{z}$ by fixing $\mathbf{z}$ and manually setting the viewpoint $v$ to arbitrary configurations. Similarly, we can query about the spatial state of a dynamic scene at time $t$ from a specific viewpoint by fixing the viewpoint and manually inputting $z^t$ at arbitrary times $t$ to the generative function. We trained a DyMON on the DR-Lvl.3 data and show qualitatively the prediction results that are queried by space-time tuples in Figure 2.

**Dynamics Replay of Scenes & Objects From Arbitrary Viewpoints** In this experiment, we give DyMON a sequence of image observations of a dynamic scene as input, and have it reply the dynamics from a novel viewpoint using the scene representations it infers from the observations. This is done by fixing the $v$ to the desired values and querying about consecutive times. As the inferred scene representations are factorized in terms of objects, we show in Figure 3 (left) that, besides the complete scene dynamics, DyMON also allows to replay the dynamics of a single object independently of the others. We present the qualitative results on the MJC-Arm datasets in Figure 3 (right) where one can see that DyMON not only replays object dynamics as global position changes, it also captures object local motions.

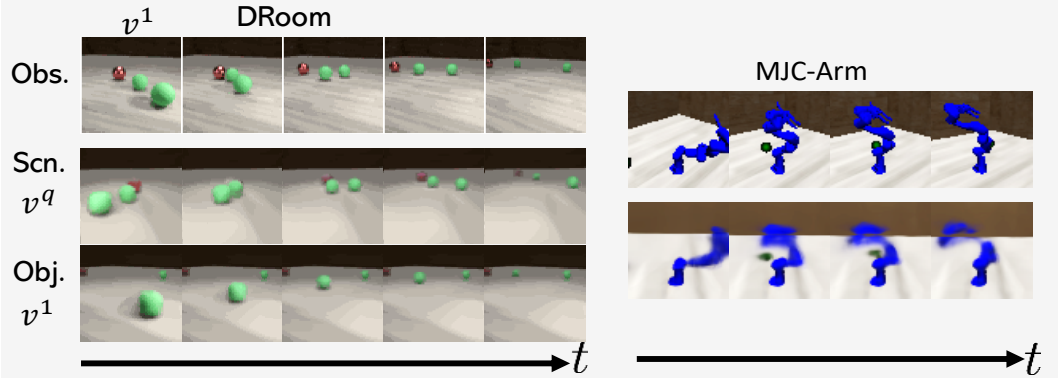


Figure 3: **Left:** DyMON performing dynamics replays on the DRoom dataset, where the first row is the observation sequence input to DyMON, second and third rows show replays of the scene dynamics (all objects' original motions) and object dynamics (just the foreground green ball moves) respectively from an arbitrary viewpoint $v^q$. **Right:** DyMON replays local motions of robot arm from an arbitrary viewpoint (top: observation, bottom: replay form a higher viewpoint).

### 5.2 Versatile Evaluation

DyMON is designed to handle object-centric representation learning in a general setting—*multi-view-dynamic-scenes*. In this section, we experiment to evaluate how well DyMON handles the specialized settings.

**DyMON vs. Dynamic Scenes** We first evaluate DyMON's performance in the *multi-view-dynamic-scene* setting in comparison to MulMON. MulMON also learns the *independent generative mechanism* of scene objects and observer, but with a strict static-scene constraint. Note that both DyMON and MulMON permit novel-view predictions of scene appearances and segmentations, this allows explicit quantification of the correctness and accuracy of the inferred scene representations. We use a mean-squared-error (MSE) measure and a mean-intersection-over-union score (mIoU) measure. We train DyMON on the DR-Lvl.3 subset and MulMON on the DR0-$|\overline{f_{\mathbf{z}}}|$ subset (because it is UNABLE to train on dynamic-scene data) and conduct comparison across the three DRoom dynamic-scene subsets (i.e. DR-Lvl.1 $\sim$ 3). Table 1a shows that, although we train MulMON on a more strict dataset, i.e. the DR0-$|\overline{f_{\mathbf{z}}}|$ dataset, DyMON still outperforms MulMON on almost all the various indicators. As neither DyMON nor MulMON impose any orders for object discovery, we used the Hungarian matching algorithm to find the best match that maximizes the mIoU score to handle the bipartite matching between the output and the Ground-truth masks.

**DyMON vs. Static Scenes** We evaluate how well it handles *multi-view-static-scene* scenarios in comparison with a specialized model, i.e. MulMON. We train and test both DyMON nad MulMON on the DR0-$|\overline{f_{\mathbf{z}}}|$ subset w.r.t. reconstructions and segmentations of both the observed and unobserved views. Table 1b summarizes the results. They show that DyMON can handle this strict constraint setting, even though it exhibits a slight performance gap compared with the specialized model.

This experiment along with the the **DyMON-versus-dynamics-scenes** experiment provides useful guidance for model selection in multi-view applications—use a specialized model in a well-controlled environment and DyMON to handle complex scenarios.

**DyMON vs. Fixed-View Observations of Dynamic Scenes** We assessed DyMON's performance on handling *single-view-dynamic-scene* observations by comparing it with GSWM, which is a specialized object-centric representation model for this specific setting, even though it is unable to achieve pixel-level segmentation. We train both DyMON and GSWM on the DR0-$|\overline{f_v}|$ subset and measure the reconstruction quality of the observations. Table 1c shows that DyMON not only outperforms GSWM in observation reconstruction, but it also permits pixel-wise segmentation which the specialized model cannot. It is worth noting that although DyMON supports well temporal interpolations, i.e. dynamics replays (as shown in Figure 3), it does not model the object dynamics nor interactions explicitly like GSWM. Therefore, it does not provide readily extrapolatable features along the time (or dynamics) axis of predicting for the future.

| | MSE↓ | | mIoU↑ | |
|---|---|---|---|---|
| Models | Obs.Rec. | Nv.Obs. | Obs.Seg. | Nv.Seg. |
| MulMON | $0.011 \pm 0.001$ | $\mathbf{0.019 \pm 0.074}$ | $0.511 \pm 0.001$ | $0.461 \pm 0.062$ |
| **DyMON** | $\mathbf{0.004 \pm 0.001}$ | $0.021 \pm 0.074$ | $\mathbf{0.717 \pm 0.000}$ | $\mathbf{0.508 \pm 0.065}$ |

(a) DyMON vs. *Multi-View-Dynamic-Scenes*

| | MSE↓ | | mIoU↑ | |
|---|---|---|---|---|
| Models | Obs.Rec. | Nv.Obs. | Obs.Seg. | Nv.Seg. |
| MulMON | $\mathbf{0.006 \pm 0.001}$ | $\mathbf{0.012 \pm 0.005}$ | $\mathbf{0.583 \pm 0.080}$ | $\mathbf{0.538 \pm 0.105}$ |
| **DyMON** | $0.014 \pm 0.001$ | $0.019 \pm 0.007$ | $0.529 \pm 0.005$ | $0.506 \pm 0.105$ |

(b) DyMON vs. *Multi-View-Static-Scenes*

| | MSE↓ | mIoU↑ |
|---|---|---|
| Models | Obs.Rec. | Obs.Seg. |
| GSWM | $0.039 \pm 0.007$ | N/A |
| **DyMON** | $\mathbf{0.014 \pm 0.011}$ | $\mathbf{0.682 \pm 0.107}$ |

(c) DyMON vs. *Single-View-Dynamic-Scenes*

Table 1: Quantitative comparisons of DyMON and two baseline models, i.e. GSWM and MulMON, in handling scenarios that the baseline models are specialized at. The models in table (a) are trained and tested on the DR0-$|\overline{f_v}|$ data, and those in (b) and (c) are trained and tested on the DR0-$|\overline{f_{\mathbf{z}}}|$ data. "Obs." tags reconstructions and segmentations that are computed for the observations and "Nv." tags that for the novel viewpoints. Mean $\pm$ stddev for 3 seeds. "N/A" denotes cases where a task is NOT supported by a model. $\uparrow$ indicates higher is better and $\downarrow$ indicates the opposite.

# 6 Conclusion

We have presented Dynamics-aware Multi-Object Network (DyMON), a method for learning object-centric representations in a *multi-view-dynamic-scene* setting. We have made two weak assumptions that allows DyMON to recover the *independent generative mechanism* of observers and scene objects from both training and testing *multi-view-dynamic-scene* data—achieving *spatial-temporal factorization*. This permits querying the predictions of scene appearances and segmentations across both space and time. As this work focuses on representing the spatial scene configurations at every specific time point, i.e. DyMON does not model dynamics explicitly so it cannot predict the future evolution of scenes, which leaves space for future exploration.

# Broader Impact

In this paper, we presented a new approach to learning unsupervised object-centric latent representations of multi-object dynamic scenes. Learning object-centric representations of dynamic scenes facilitates efficient spatial-temporal reasoning of the surrounding environments, which can potentially support applications of various magnitudes, i.e., the development of augmented/virtual reality applications to object detection and tracking. Real-world scenarios usually involve both dynamic objects (either position changes or shape changes) and moving observers, but for simplicity researchers assume that the environment is static, which is not the case. Augmented/virtual reality applications have greatly suffered from this ill-posed assumption. A significant improvement in how to deal with dynamic scenes will open up new opportunities for augmented reality in sports and medical/surgical treatments.

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# Checklist

*(1) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?*
- Yes

*(2) Have you read the ethics review guidelines and ensured that your paper conforms to them?*
- Yes.

(3) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?
- Yes.

(4) Have you read the ethics review guidelines and ensured that your paper conforms to them?
- Yes

(5) Did you discuss any potential negative societal impacts of your work?
- Yes. See Sec. 6.

(6) Did you describe the limitations of your work?
- Yes. See Sec. 5.2 and the Conlusion section.

(7) Did you state the full set of assumptions of all theoretical results?
- Yes. See Sec. 3.1

(8) Did you include complete proofs of all theoretical results?
- N/A.

(9) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)?
- Yes. We included them in the supplemental materials.

(10) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)?
- Yes. We provided the full implmentation details in the appendix.

(11) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)?
- Yes. We presented all the quantitative results in the form of "mean$\pm$std" in the main paper.

(12) Did you include the amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)?
- Yes. See Appendix B.

(13) If your work uses existing assets, did you cite the creators?
- Yes. We used the CLEVR envieronment and we cited the original paper.

(14) Did you mention the license of the assets?
- Yes. We mentioned it in our appendix.

(15) Did you include any new assets either in the supplemental material or as a URL?
- Yes. We included it in our appendix.

(16) Did you discuss whether and how consent was obtained from people whose data you're using/curating?
- N/A.

(17) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content?
- N/A.

(18) Did you include the full text of instructions given to participants and screenshots, if applicable?
- N/A.

(19) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable?
- N/A.

(20) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation?
- N/A.