REASONING ABOUT PHYSICAL INTERACTIONS WITH OBJECT-CENTRIC MODELS

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ABSTRACT

Object-based factorizations provide a useful level of abstraction for interacting with the world. Building explicit object representations, however, often requires supervisory signals that are difficult to obtain in practice. We present a paradigm for learning object-centric representations for physical scene understanding without direct supervision of object properties. Our model, object-oriented prediction and planning (O2P2), jointly learns a perception function to map from image observations to object representations, a pairwise physics interaction function to predict the time evolution of a collection of objects, and a rendering function to map objects back to pixels. For evaluation, we consider not only the accuracy of the physical predictions of the model, but also its utility for downstream tasks that require an actionable representation of intuitive physics. After training our model on an image prediction task, we can use its learned representations to build block towers more complicated than those observed during training.

1 INTRODUCTION

Consider the castle made out of toy blocks in Figure 1a. Can you imagine how each block was placed, one-by-one, to build this structure? Humans possess a natural physical intuition that aids in the performance of everyday tasks. This physical intuition can be acquired, and refined, through experience. Despite being a core focus of the earliest days of artificial intelligence and computer vision research (Roberts, 1963; Winston, 1970), a similar level of physical scene understanding remains elusive for machines.

Cognitive scientists argue that humans' ability to interpret the physical world derives from a richly structured apparatus. In particular, the perceptual grouping of the world into objects and their relations constitutes *core knowledge* in cognition (Spelke & Kinzler, 2007). While it is appealing to apply such an insight to contemporary machine learning methods, it is not straightforward to do so. A fundamental challenge is the design of an interface between the raw, often high-dimensional observation space and a structured, object-factorized representation. Existing works that have investigated the benefit of using objects have either assumed that an interface to an idealized object space already exists or that supervision is available to learn a mapping between raw inputs and relevant object properties (for instance, category, position, and orientation).

Assuming access to training labels for all object properties is prohibitive for at least two reasons. The most apparent concern is that curating supervision for all object properties of interest is difficult to scale for even a modest number of properties. More subtly, a representation based on semantic attributes can be limiting or even ill-defined. For example, while the size of an object in absolute terms is unambiguous, its orientation must be defined with respect to a canonical, class-specific orientation. Object categorization poses another problem, as treating object identity as a classification problem inherently limits a system to a predefined vocabulary.

In this paper, we propose object-oriented prediction and planning (O2P2), in which we train an object representation suitable for physical interactions without supervision of object attributes. Instead of direct supervision, we demonstrate that segments or proposal regions in video frames, without correspondence between frames, are sufficient supervision to allow a model to reason effectively about intuitive physics. We jointly train a perception module, an object-factorized physics engine, and a neural renderer on a physics prediction task with pixel generation objective. We evaluate our learned model not only on the quality of its predictions, but also on its ability to use the learned representations for tasks that demand a sophisticated physical understanding.

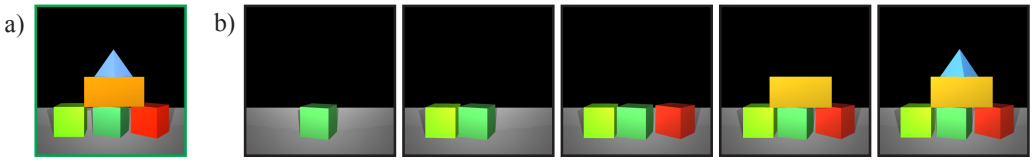


Figure 1: **(a)** A toy block castle. **(b)** Our model's build of the observed castle, using its learned object representations as a guide during planning.

2 OBJECT-ORIENTED PREDICTION AND PLANNING (O2P2)

In this section, we describe a method for learning object-based representations suitable for planning in physical reasoning tasks. As opposed to much prior work on object-factorized scene representations (Section 3), we do not supervise the content of the object representations directly by way of labeled attributes (such as position, velocity, or orientation). Instead, we assume access only to segments or region proposals for individual video frames. Since we do not have labels for the object representations, we must have a means for converting back and forth between images and object representations for the purposes of training. O2P2 consists of three components, which are trained jointly:

- A **perception** module that maps from an image to an object encoding. The perception module is applied to each object segment independently.
- A **physics** engine to predict the time evolution of a set of objects. We formulate the engine as a sum of pairwise object interactions plus a single-object transition function.
- A **rendering** engine that produces an image prediction from a variable number of objects. We first predict an image and single-channel heatmap for each object. We then combine all of the object images according to the weights in their heatmaps at every pixel location to produce a single composite image.

A high-level overview of the model is shown in Figure 2c. Below, we give details for the design of each component and their subsequent use in a model-based planning setting.

2.1 PERCEPTION MODULE

The perception module is a convolutional encoder that maps from an image observation of an object to a latent object representation vector. At timestep t, the input to the module is a stack of N images, where N is the number of segments or proposals per image. The output is one object vector per segment, $\mathbf{o_t} = (o_{t,1}, o_{t,2}, \ldots, o_{t,N})$. Since we do not have ground-truth object states as supervision, we cannot train the perception module independently from the other modules. It must be trained jointly with the physics or rendering engine.

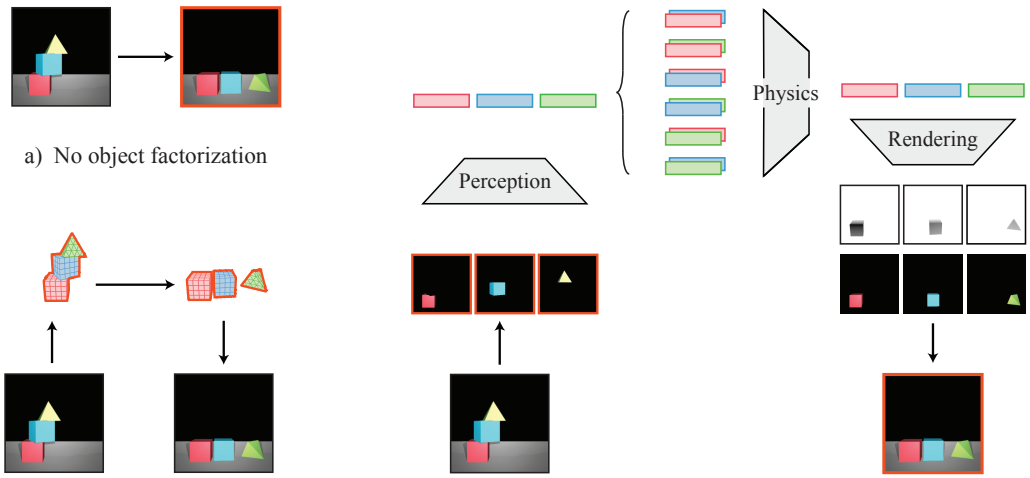
2.2 PHYSICS ENGINE

The physics engine learns to simulate a collection of object representations to predict their configuration at a later time. As in Chang et al. (2016); Watters et al. (2017), we consider the interactions of all pairs of object vectors. The physics engine contains two learned subcomponents: a transition function f_{trans} applied to each object representation independently, and an interaction function f_{interact} applied to all pairs of object representations. Given $\mathbf{o}_t$, a set of object vectors from the perception module at time t, the physics engine outputs $\mathbf{o}_{t+1}$. For the ith object,

$$o_{t+1,i} = f_{\text{trans}}(o_{t,i}) + \sum_{j \neq i} f_{\text{interact}}(o_{t,i}, o_{t,j}) + o_{t,i}$$

where both f_{trans} and f_{interact} are instantiated as multilayer perceptrons.

In this work we use physics prediction as a means to learn object representations suitable for planning actions, not as an end goal itself. For this purpose it is more important to know the resulting long-term effect of an interaction rather than estimating the configuration of a scene at every timestep. To that end, instead of training the physics engine to predict object representations at a fixed time in the future, we predict the steady-state representations after accounting for physics simulation. This simplification avoids the complications of long-horizon sequential prediction while retaining the information relevant to planning under physical laws and constraints. More precisely, for a collection of object representations we need only consider the initial and final configurations. We denote these as $\mathbf{o}_0$ and $\mathbf{o}_1$, respectively.



a) No object factorization

b) Object property supervision

c) O2P2: Object factorization without object property supervision

Figure 2: We divide physical understanding tasks into three distinct paradigms. **(a)** The first approach makes the fewest assumptions, posing prediction tasks as an instance of image-to-image translation. **(b)** The second uses ground-truth labels of object properties to supervise a learning algorithm that can map to the space of a traditional or learned physics engine. **(c)** O2P2, like (b), employs an object factorization and the functional structure of a physics engine, but like (a), does not assume access to supervision of object properties. Without object-level supervision, we must jointly learn a perception function to map from images to objects, a physics engine to simulate a collection of objects, and a rendering engine to map a set of objects back to a single composite image prediction. In all three approaches, we highlight the key supervision in orange.

2.3 Rendering Engine

Because our only supervision occurs at the pixel level, to train our model we learn to map all object-vector predictions back to images. A challenge here lies in designing a function which constructs a single image from an entire collection of objects. The learned renderer consists of two networks, both instantiated as convolutional decoders. The first network predicts an image independently for each input object vector. Composing these images into a single reconstruction amounts to selecting which object is visible at every pixel location. In a traditional graphics engine, this would be accomplished by calculating a depth pass at each location and rendering the nearest object.

To incorporate this structure into our learned renderer, we use the second decoder network to produce a single-channel heatmap for each object. The composite scene image is a weighted average of all of the object-specific renderings, where the weights come from the negative of the predicted heatmaps. In effect, objects with lower heatmap predictions at a given pixel location will be more visible than objects with higher heatmap values. This encourages lower heatmap values for nearer objects. Although this structure is reminiscent of a depth pass in a traditional renderer, the comparison should not be taken literally; the model is only supervised by composite images and no true depth maps are provided during training.

2.4 Planning with Learned Models

We now describe the use of our perception, physics, and rendering modules in the representative planning task depicted in Figure 1, in which the goal is to build a block tower to match an observed image. Here, matching a tower does not refer simply to producing an image from the rendering engine that looks like the observation. Instead, we consider the scenario where the model must output a sequence of actions to construct the configuration.

This setting is much more challenging because there is an implicit sequential ordering to building such a tower. For example, the bottom cubes must be placed before the topmost triangle. O2P2 was trained solely on a pixel-prediction task, in which it was never shown such valid action orderings (or any actions at all). However, these orderings are essentially constraints on the physical stability of intermediate towers, and should be derivable from a model with sufficient understanding of physical interactions.

Although we train a rendering function as part of our model, we guide the planning procedure for constructing block towers solely through errors in the learned object representation space. The procedure is as follows:

1. The perception module **encodes** the goal image into a set of object representations $\mathbf{o}_1^{\text{targ}}$.
2. We **sample** actions of the form `(shape, position, orientation, color)`, where `shape` is categorical and describes the type of block, and the remainder of the action space is continuous and describes the block's appearance and where it should be dropped.
3. We **evaluate** the samples by likewise encoding them as object vectors and comparing them to $\mathbf{o}_1^{\text{targ}}$. We view each action sample as an image (analogous to observing a block held in place before dropping it) and use the perception module to produce object vectors from each sample, $\mathbf{o}_0^{\text{pred}}$. Because the actions selected should produce a stable tower, we run all sampled object representations through the physics engine to yield $\mathbf{o}_1^{\text{pred}}$ before comparing to $\mathbf{o}_1^{\text{targ}}$. Object representations are compared using mean squared error (MSE).
4. Using the action sampler and evaluation metric, we **select** actions using the cross-entropy method (CEM) (Rubinstein & Kroese, 2004) starting from a uniform distribution. At each time step, after selecting the action that minimizes loss to one of the observed objects in the set of vectors $\mathbf{o}_1^{\text{targ}}$, we **execute** that action in MuJoCo (Todorov et al., 2012). We continue this procedure, iteratively re-planning and executing actions, until there are as many actions in the executed sequence as there are objects in the target image.

3 Related Work

Our work is situated at the intersection of two distinct paradigms. In the first, a rigid notion of object representation is enforced via supervision of object properties (such as size, position, and identity). In the second, scene representations are not factorized at all, so no extra supervision is required. These two approaches have been explored in a variety of domains.

Image and video understanding The insight that static observations are physically stable configurations of objects has been leveraged to improve 3D scene understanding algorithms. For example, Zheng et al. (2014); Gupta et al. (2010); Shao et al. (2014) build physically-plausible scene representations using such stability constraints. Some approaches explicitly define energy functions to represent the stability of a scene explanation (Jia et al., 2015), whereas others encode scenes in a markup-style language suitable for consumption by a physics engine such that it may be simulated directly (Wu et al., 2017). We consider a scenario in which the physical representations are learned from data rather than supervised directly to encode specific content.

General unsupervised latent disentanglement (as opposed to object-centric factorization) has been explored by Chen et al. (2016); Higgins et al. (2017); Kulkarni et al. (2015) using mutual information losses, independence criteria, and constrained update rules. There has also been much attention on inferring object-factorized, or otherwise disentangled, representations of images independently of physical constraints (Eslami et al., 2016; Greff et al., 2017). Object-centric scene decompositions have also been considered as a potential state representation in reinforcement learning (Diuk et al., 2008; Scholz et al., 2014; Devin et al., 2017; Goel et al., 2018; Keramati et al., 2018). In contrast, we are specifically concerned with the problem of predicting and reasoning about physical phenomena, and show that a model capable of this can also be employed for decision making.

Learning and inferring physics Fragkiadaki et al. (2016); Watters et al. (2017); Chang et al. (2016) have shown approaches to learning a physical interaction engine from data. Hamrick et al. (2011) use a traditional physics engine, performing inference over object parameters, and show that such a model can account for humans' physical understanding judgments. We consider a similar physics formulation, whereby update rules are composed of sums of pairwise object-interaction functions, and incorporate it into a training routine that does not have access to ground truth supervision in the form of object parameters (such as position or velocity).

An alternative to using a traditional physics engine (or a learned object-factorized function trained to approximate one) is to treat physics prediction as an image-to-image translation or classification problem. In contrast to these prior methods, we consider not only the accuracy of the predictions of our model, but also its utility for downstream tasks that are intentionally constructed to evaluate its ability to acquire an actionable representation of intuitive physics. Comparing with representative

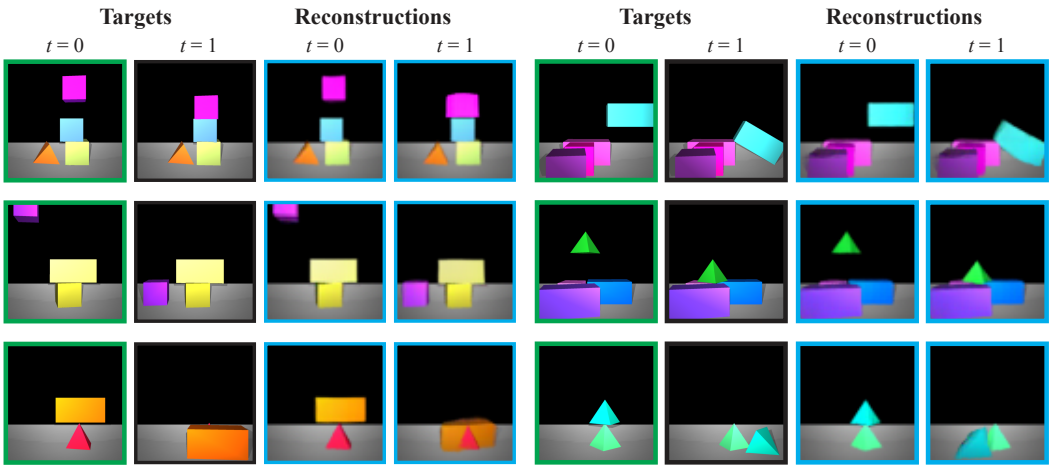


Figure 3: Given an observed image I_0 at $t = 0$, our model predicts a set of object representations $\mathbf{o}_0$, simulates the objects with a learned physics engine to produce $\mathbf{o}_1$, and renders the resulting predictions to get $\hat{I}_1$, the scene's appearance at a later time. We use the convention (in all figures) that observations are outlined in green, other images rendered with the ground-truth renderer are outlined in black, and images rendered with our learned renderer are outlined in blue.

Table 1: Accuracy (%) of block tower builds by our approach and the four comparison models.

No physics	SAVP	Ours	Oracle (pixels)	Oracle (objects)
0	24	76	71	92

video prediction (Lee et al., 2018; Babaeizadeh et al., 2018) and physical prediction (Ehrhardt et al., 2017; Mottaghi et al., 2016; Li et al., 2017; Lerer et al., 2016) methods, our approach achieves substantially better results at tasks that require building structures out of blocks.

4 Experimental Evaluation

In our experimental evaluation, we aim to answer the following questions, (1) After training solely on physics prediction tasks, can O2P2 reason about physical interactions in an actionable and useful way? (2) Does the implicit object factorization imposed by O2P2's structure provide a benefit over an object-agnostic black-box video prediction approach? (3) Is an object factorization still useful even without supervision for object representations?

4.1 Learning object representations

We train O2P2 on a distribution of object configurations that differs from the distribution of blocks on the downstream evaluation task. This allows us to determine the extent to which our object representations reflect the underlying physical laws of a domain versus task-specific information about the data on which it was trained. It also has the added benefit of being easier to collect training data of object interactions when the exact object configurations are not required to match the task of interest.

To generate training data, we simulate dropping one to five blocks on top of a fixed platform. We vary the position, color, and orientation of three block varieties (cubes, rectangles, and triangles). In total, we collect 60,000 training images using the MuJoCo simulator. Since our physics engine does not make predictions at every timestep (Section 2.2), we only record the initial image I_0 and the final image I_1 of a simulation after all blocks have come to rest.

For each training image pair (I_0, I_1), we predict object representations $\mathbf{o}_0 = f_{\text{percept}}(I_0)$ from the first observation, and predict the future object representations $\mathbf{o}_1 = f_{\text{physics}}(\mathbf{o}_0)$ with the learned physics engine. The rendering engine then predicts an image $\hat{I}_t = f_{\text{render}}(\mathbf{o}_t)$ from each of the object representations. We compare each image prediction $\hat{I}_t$ to its ground-truth counterpart using both $\mathcal{L}_2$ distance and a perceptual loss in the feature space of the VGG network, $\mathcal{L}_{\text{VGG}}$ (Simonyan & Zisserman, 2014), as described by Johnson et al. (2016). The perception module is supervised by the reconstruction of I_0, the physics engine is supervised by the reconstruction of I_1, and the

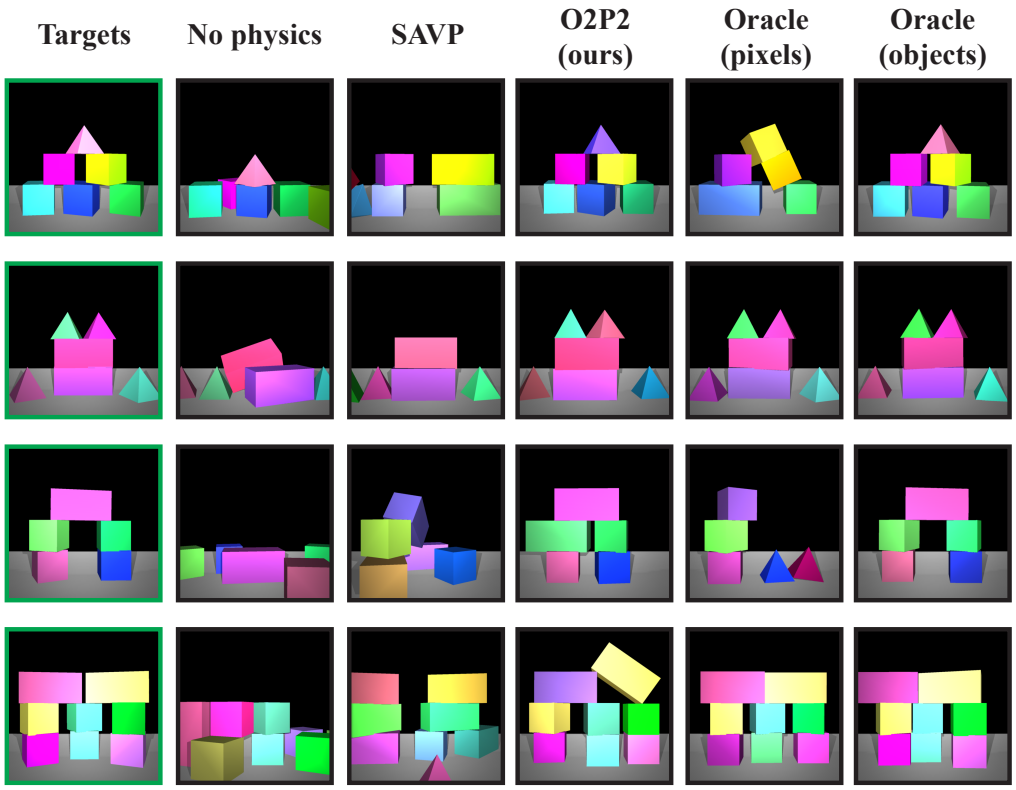


Figure 4: Given an observed block tower, O2P2 can use its learned object representations to guide planning to recreate the configuration. Our model never compares directly to the observation in image space, only through its object representations. We compare to an ablation, an object-agnostic video prediction model, and two 'oracles' with access to the ground-truth simulator.

rendering engine is supervised by the reconstruction of both images. Specifically,

$$\mathcal{L}_{\text{percept}}(\cdot) = \mathcal{L}_2(\hat{I}_0, I_0) + \mathcal{L}_{\text{VGG}}(\hat{I}_0, I_0), \tag{1}$$

$$\mathcal{L}_{\text{physics}}(\cdot) = \mathcal{L}_2(\hat{I}_1, I_1) + \mathcal{L}_{\text{VGG}}(\hat{I}_1, I_1), \tag{2}$$

$$\mathcal{L}_{\text{render}}(\cdot) = \mathcal{L}_{\text{percept}}(\cdot) + \mathcal{L}_{\text{physics}}(\cdot). \tag{3}$$

Representative results on held-out random configurations are shown in Figure 3. Even when the model's predictions at $t = 1$ differ from the ground truth image (such as in the last row of the figure), the physics engine produces a plausible simulation of the scene from the observation at $t = 0$.

4.2 Matching observed towers

After training O2P2 on the random configurations of blocks, we fix its parameters and employ the planning procedure as described in Section 2.4 to build tower configurations observed in images. We also evaluate the following models as comparisons:

- **No physics** is an ablation of our model that does not run the learned physics engine, but instead simply sets $\mathbf{o}_1 = \mathbf{o}_0$
- stochastic adversarial video prediction (**SAVP**), a block-box video prediction model which does not employ an object factorization Lee et al. (2018). The cost function of samples is evaluated on the image pixels directly. The sampling-based planning routine is otherwise the same as in our approach.
- **Oracle (pixels)** uses the MuJoCo simulator to evaluate samples instead of our learned physics and graphics engines. The cost of a block configuration is evaluated directly in pixel space.
- **Oracle (objects)** also uses the MuJoCo simulator, but has access to segmentation masks on the input images while evaluating the cost of proposals. Constraining proposed actions to account for

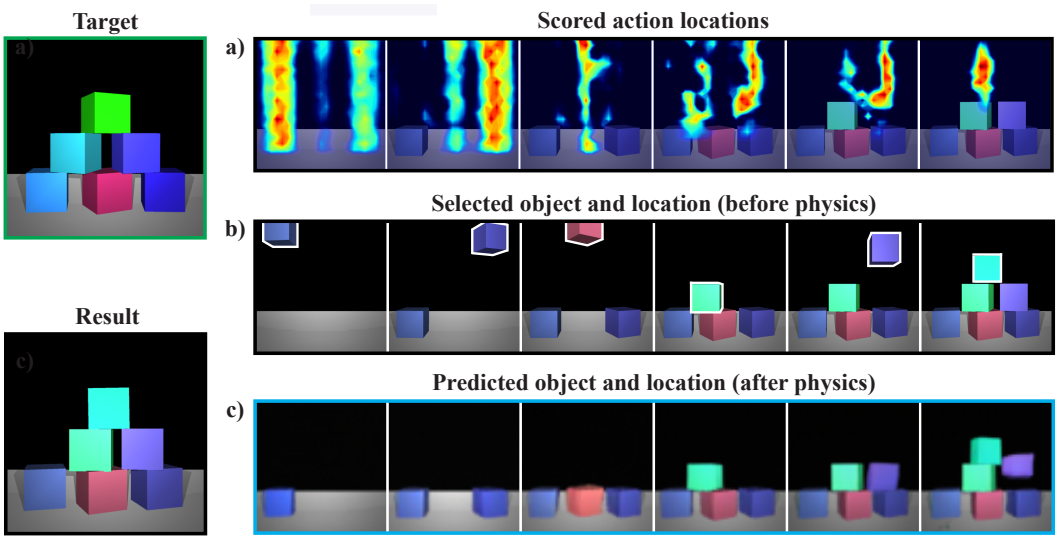


Figure 5: (a) Visualization of scored locations for dropping an object at each timestep. Because O2P2 simulates physics before selecting an action, it is able to plan a sequence of stable actions. (b) The selected block and drop position from the scored samples, outlined in white. (c) The prediction from our physics model of the result of running physics on the selected block.

only a single object in the observation resolves some of the inherent difficulties of using pixel-wise loss functions.

Qualitative results of all models are shown in Figure 4 and a quantitative evaluation is shown in Table 1. We evaluate tower stacking success by greedily matching the built configuration to the ground-truth state of the target tower, and comparing the maximum object error (defined on its position, identity, and color) to a predetermined threshold. Although the threshold is arbitrary in the sense that it can be chosen low enough such that all builds are incorrect, the relative ordering of the models is robust to changes in this value. All objects must be of the correct shape for a built tower to be considered correct, meaning that our third row prediction in Figure 4 is incorrect because a green cube was mistaken for a green rectangle.

While SAVP makes accurate predictions on the training data, it does not generalize well to these more complicated configurations with more objects per frame. As such, its stacking success is low. Physics simulation is crucial to our model, as our No-physics ablation fails to stack any towers correctly. We explore the role of physics simulation in the stacking task in Section 4.3. The 'oracle' model with access to the ground-truth physics simulator is hampered when making comparisons in pixel space. A common failure mode of this model was to drop a single large block on the first step to cover the visual area of multiple smaller blocks in the target image. This scenario is depicted by the blue rectangle in the first row of Figure 4 in the Oracle (pixels) column.

4.3 The Importance of Understanding Physics

Figure 5 depicts the entire planning and execution procedure for O2P2 on a pyramid of six blocks. At each step, we visualize the process by which our model selects an action by showing a heatmap of scores (negative MSE) for each action sample according to the sample's (x, y) position (Figure 5a). Although the model is never trained to produce valid action decisions, the planning procedure selects a physically stable sequence of actions. For example, at the first timestep, the model scores three x-locations highly, corresponding to the three blocks at the bottom of the pyramid. It correctly determines that the height at which it releases a block at any of these locations does not particularly matter, since the block will drop to the correct height after running the physics engine. Figure 5b shows the selected action at each step, and Figure 5c shows the model's predictions about the configuration after releasing the sampled block.

Similar heatmaps of scored samples are shown for the No-physics ablation of our model in Figure 6. Because this ablation does not simulate the effect of dropping a block, its highly-scored action samples correspond almost exactly to the actual locations of the objects in the target image. Further, without physics simulation it does not implicitly select for stable action sequences; there is nothing to prevent the model from selecting the topmost block of the tower as the first action.

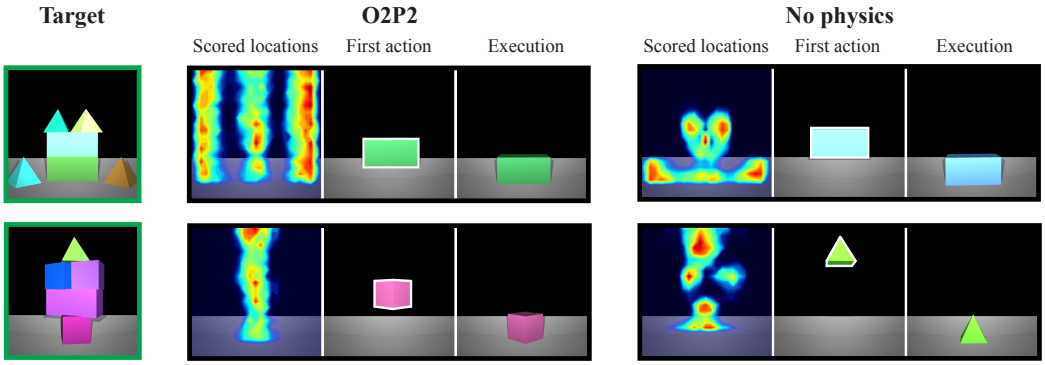


Figure 6: Heatmaps showing sampled action scores for the initial action given a target block tower. O2P2's scores reflect that the objects resting directly on the platform must be dropped first, and that they may be dropped from any height because they will fall to the ground. The No-physics ablation, on the other hand, does not implicitly represent that the blocks need to be dropped in a stable sequence of actions because it does not predict the blocks moving after being released.

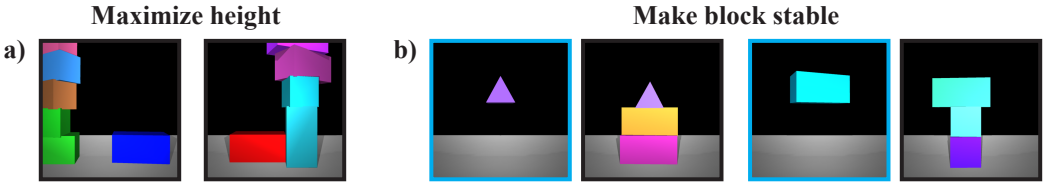


Figure 7: O2P2 being used to plan for the alternate goals of (a) maximizing the height of a tower and (b) making an observed block stable by use of any other blocks.

Planning for alternate goals By implicitly learning the underlying physics of a domain, our model can be used for a variety of tasks besides matching observed towers. In Figure 7a, we show our model's representations being used to plan a sequence of actions to maximize the height of a tower. There is no observation for this task, and the action scores are calculated based on the highest non-zero pixels after rendering samples with the learned renderer. In Figure 7b, we consider a similar sampling procedure as in the tower-matching experiments, except here only a single *unstable* block is shown. Matching a free-floating block requires planning with O2P2 for multiple steps at once.

5 Implementations Details

Objects were represented as 256-dimensional vectors. The perception module had four convolutional layers of {32, 64, 128, 256} channels, a kernel size of 4, and a stride of 2 followed by a single fully-connected layer with output size matching the object representation dimension. Both MLPs in the physics engine had two hidden layers each of size 512. The rendering networks had convolutional layers with {128, 64, 32, 3} channels (or 1 output channel in the case of the heatmap predictor), kernel sizes of {5, 5, 6, 6}, and strides of 2. We used the Adam optimizer (Kingma & Ba, 2015) with a learning rate of 1e-3.

6 Conclusion

We introduced a method of learning object-centric representations suitable for physical interactions. These representations did not assume the usual supervision of object properties in the form of position, orientation, velocity, or shape labels. Instead, we relied only on segment proposals and a factorized structure in a learned physics engine to guide the training of such representations. We demonstrated that this approach is appropriate for a standard physics prediction task. More importantly, we showed that this method gives rise to object representations that can be used for difficult planning problems, in which object configurations differ from those seen during training, without further adaptation. We evaluated our model on a block tower matching task and found that it outperformed object-agnostic approaches that made comparisons in pixel-space directly.

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