Brick-by-Brick: Combinatorial Construction with Deep Reinforcement Learning

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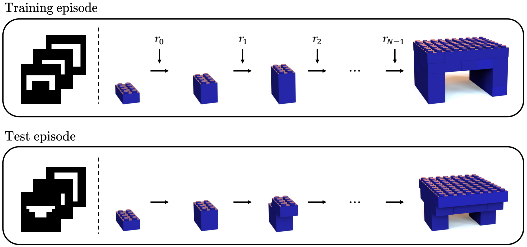
Introduction

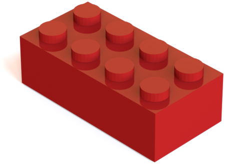


- Introduce an interesting yet challenging problem that is defined on a combinatorial space, characterized by discrete variables and their combinations.
  - Sequentially assemble unit primitives (i.e., LEGO bricks), given only incomplete target information (i.e., a 2D image or multiple views of a target object).
  - Require a comprehensive understanding of incomplete target information and long-term planning to append each brick efficiently.

Introduction

- Devise a reinforcement learning (RL) approach along with the absence of sequence-level supervision.
  - Express a brick combination as graph representation, where node and edge correspond to a single brick and a connection between two bricks, respectively.
  - In this domain, however, struggle to handle both an indefinite action space and the existence of many invalid actions when applying RL.
  - To resolve the aforementioned issues, adopt an action validation network that filters invalid actions to an actor-critic network.

Combinatorial Construction



- A 2×4 brick as a unit primitive, which has eight studs and their fit cavities.
- Consistently growing possible positions to assemble a brick.
- With only six 2×4 bricks, 915,103,765 combinations possible [Eilers, 2016].

[Eilers 2016] S. Eilers. The LEGO counting problem. *The American Mathematical Monthly*, 123(5):415–426, 2016.

Combinatorial Construction: Assumptions

- Every connection types must follow a fixed rule.

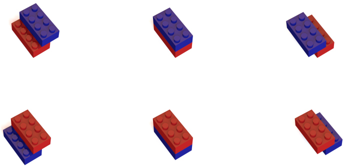


Figure 1: Example of available offsets.

- No bricks mutually overlap.

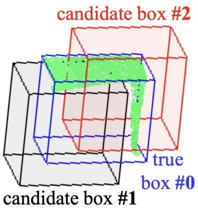


Figure 2: Obtained from [Yang et al., 2019]

[Yang et al. 2019] B. Yang et al. Learning object bounding boxes for 3D instance segmentation on point clouds. In *Advances in Neural Information Processing Systems (NeurIPS)*, volume 32, pages 6740–6749, 2019.

Combinatorial Construction: Action Space

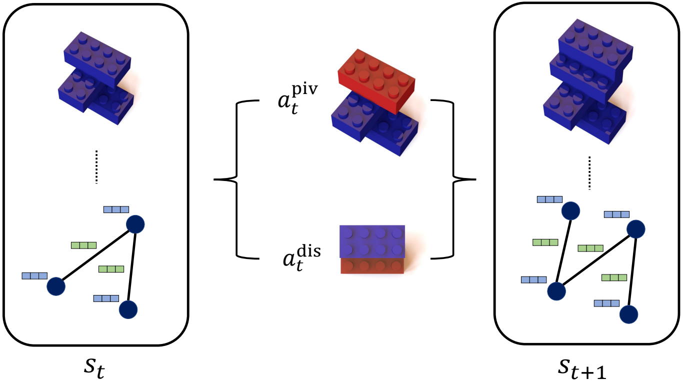


Figure 3: Successive action space.

Combinatorial Construction: Overall Scenario

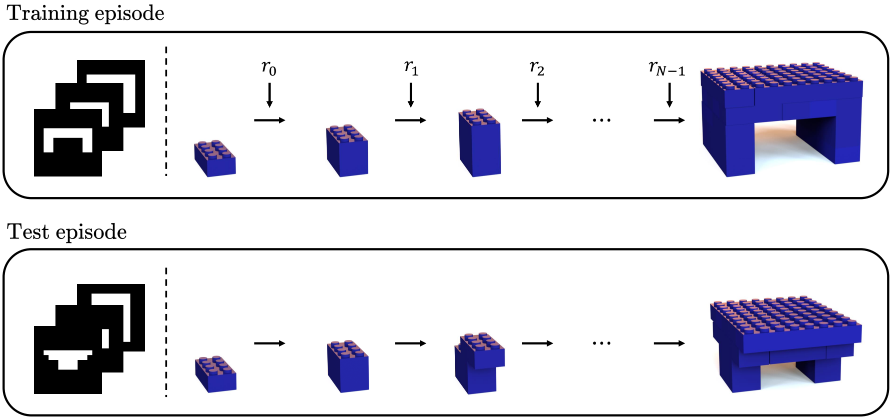


Figure 4: Training and test episodes of combinatorial construction.

Related Work on Combinatorial Construction

Table 1: Analysis of related work in terms of state representation, supervision, conditioning, the type of target objects, and action validation. CE and IoU stand for cross-entropy and intersection over union with respect to volumetric comparisons.

Method	**State**	**Supervision**	**Conditioning**	**Target**	**Action Validation**
Hamrick et al. [2018]	Image	Task-dependent	N/A	2D	Implicit
Bapst et al. [2019]	Object/Image	Task-dependent	Object and/or image	2D	Implicit
Kim et al. [2020]	Set	Overlap	Exact target volume	3D	Sampling
Thompson et al. [2020]	Graph	Step-wise CE	One-hot class info.	3D	Implicit
Brick-by-Brick (B^3, ours)	Graph/Image	IoU	Image or set of images	3D	Pretrained

[Hamrick et al., 2018] J. B. Hamrick et al. Relational inductive bias for physical construction in humans and machines. In *Proceedings of the Annual Conference of the Cognitive Science Society (CogSci)*, pages 1773–1778, Madison, Wisconsin, USA, 2018.

[Bapst et al., 2019] V. Bapst et al. Structured agents for physical construction. In *Proceedings of the International Conference on Machine Learning (ICML)*, pages 464–474, Long Beach, California, USA, 2019.

[Kim et al., 2020] J. Kim et al. Combinatorial 3D shape generation via sequential assembly. In *Neural Information Processing Systems Workshop on Machine Learning for Engineering Modeling, Simulation, and Design (ML4Eng)*, Virtual, 2020.

[Thompson et al., 2020] R. Thompson et al. Building LEGO using deep generative models of graphs. In *Neural Information Processing Systems Workshop on Machine Learning for Engineering Modeling, Simulation, and Design (ML4Eng)*, Virtual, 2020.

Brick-by-Brick

- Suppose that **target information** $\mathcal{T}$, i.e., a single binary image or a set of three binary images from different views of a target object, is given as partial information.

- Represent each t-th **state** s_t of the MDP as a tuple of a directed graph G_t composed of t bricks and target information $\mathcal{T}$, i.e., $s_t = (G_t, \mathcal{T})$.

- With t bricks assembled, define an **action** $a_t = (a_t^{\text{piv}}, a_t^{\text{off}})$ where a_t^{piv} is to select a pivot brick and a_t^{off} is to select an offset with respect to the pivot brick.

- Transform the combination of currently assembled bricks into the occupancy of the voxels and measure the overlap between them as a **reward function**:

$$\Delta\text{IoU}(\mathbf{C}_t, \mathbf{T}) = \frac{\text{vol}(\mathbf{C}_t \cap \mathbf{T})}{\text{vol}(\mathbf{C}_t \cup \mathbf{T})} - \frac{\text{vol}(\mathbf{C}_{t-1} \cap \mathbf{T})}{\text{vol}(\mathbf{C}_{t-1} \cup \mathbf{T})}, \tag{1}$$

where $\mathbf{C}_t$, $\mathbf{C}_{t-1}$, and $\mathbf{T}$ are the occupied voxels at timestep t, timestep $t-1$, and a desired target, respectively. Note that $\text{vol}(\cdot)$ is a function that measures a volume.

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Brick-by-Brick

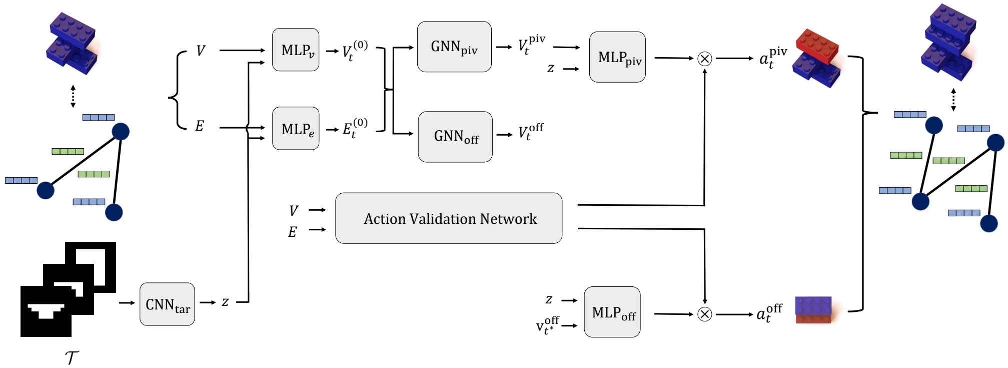


Figure 5: An overview of our proposed method B^3. State input $s_t = (G_t, \mathcal{T})$ is embedded and passed through GNNs and MLPs to predict action a_t that consists of pivot brick indicator a_t^{piv} and offset a_t^{off}. The red brick in both a_t^{piv} and offset a_t^{off} indicates the chosen brick.

Experiments: MNIST Construction

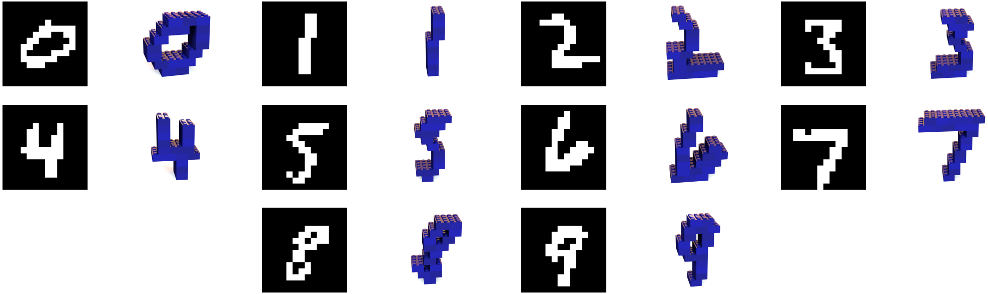
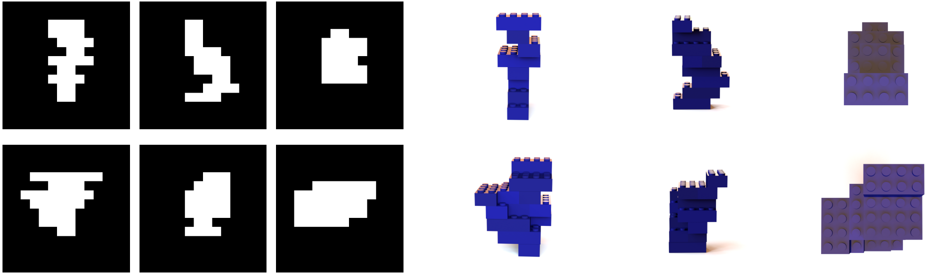


Figure 6: Qualitative results on MNIST construction.

Experiments: Randomly-Assembled Object Construction



(a) Target images (b) Constructed object from three viewpoints

Figure 7: Qualitative results on randomly-assembled object construction.

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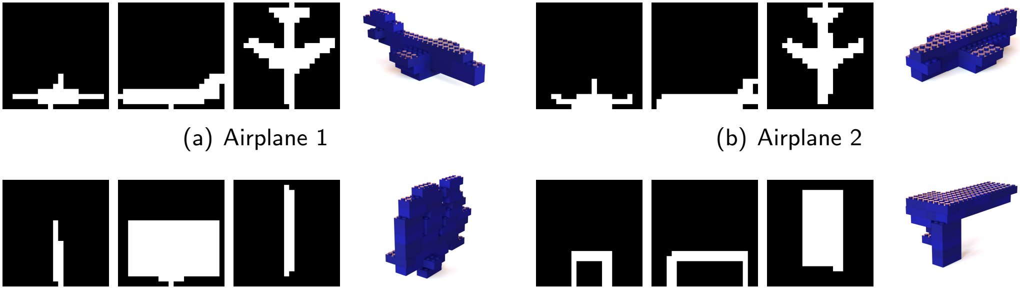
Experiments: ModelNet Construction

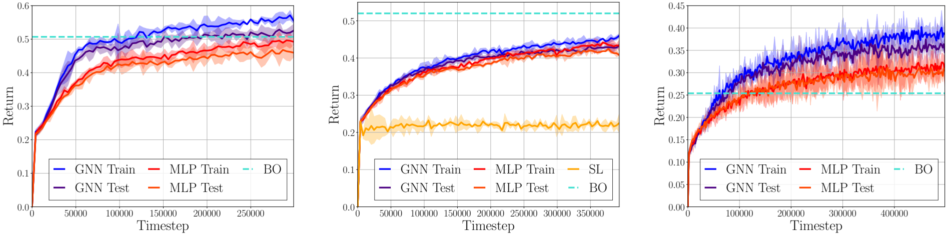


(a) Airplane 1 (b) Airplane 2

(c) Monitor (d) Table

Figure 8: Qualitative results on ModelNet construction.

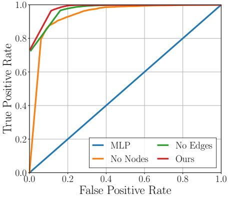
Experiments: Episode Return Curves



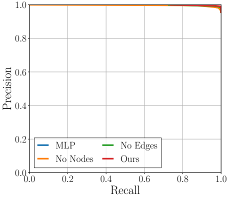
(a) MNIST (b) Randomly-Assembled (c) ModelNet

Figure 9: Episode return curves vs. timesteps in different setups. The curves measured by training and test episodes are reported by repeating 3 times with different seeds.

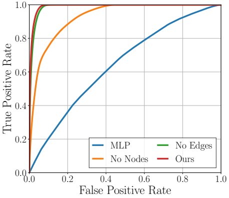
Experiments: Analysis on Action Validation Network



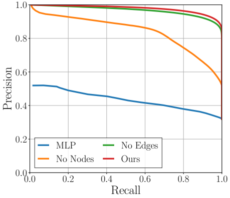
(a) Pivot ROC



(b) Pivot PR



(c) Offset ROC



(d) Offset PR

Figure 10: ROC and PR curves for an action validation network.

Discussion and Limitations

- Open a new line of research on sequential and combinatorial construction problem, as explained in Table 1.
- Limit to use a 2×4 LEGO brick as a unique unit primitive.
- Need to investigate more realistic rewards such as stability and feasibility, because our method finds a way to construct a 3D object.

Conclusion

- In this work, propose a novel problem formulation, combinatorial construction, which asks the agent to construct an object sequentially.
- Adopt RL by defining a state as graph-structured representation to express assembled bricks and their connections.
- Successfully construct a 3D object in the presence of growing action space and massive invalid actions, where incomplete target information is given.
- Demonstrate that our method can construct objects in various construction scenarios and provide detailed analysis of our action validation network.

Thank you.

References I

V. Bapst, A. Sanchez-Gonzalez, C. Doersch, K. Stachenfeld, P. Kohli, P. Battaglia, and J. Hamrick. Structured agents for physical construction. In *Proceedings of the International Conference on Machine Learning (ICML)*, pages 464–474, Long Beach, California, USA, 2019.

S. Eilers. The LEGO counting problem. *The American Mathematical Monthly*, 123(5):415–426, 2016.

J. B. Hamrick, K. R. Allen, V. Bapst, T. Zhu, K. R. McKee, J. B. Tenenbaum, and P. W. Battaglia. Relational inductive bias for physical construction in humans and machines. In *Proceedings of the Annual Conference of the Cognitive Science Society (CogSci)*, pages 1773–1778, Madison, Wisconsin, USA, 2018.

J. Kim, H. Chung, J. Lee, M. Cho, and J. Park. Combinatorial 3D shape generation via sequential assembly. In *Neural Information Processing Systems Workshop on Machine Learning for Engineering Modeling, Simulation, and Design (ML4Eng)*, Virtual, 2020.

R. Thompson, G. Elahe, T. DeVries, and G. W. Taylor. Building LEGO using deep generative models of graphs. In *Neural Information Processing Systems Workshop on Machine Learning for Engineering Modeling, Simulation, and Design (ML4Eng)*, Virtual, 2020.

B. Yang, J. Wang, R. Clark, Q. Hu, S. Wang, A. Markham, and N. Trigoni. Learning object bounding boxes for 3D instance segmentation on point clouds. In *Advances in Neural Information Processing Systems (NeurIPS)*, volume 32, pages 6740–6749, 2019.