Combinatorial 3D Shape Generation via Sequential Assembly

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Overview

- 3D shape generation via *sequential assembly* mimics a human assembling process, by allocating a budget of primitives given.
- We solve a sequential problem with Bayesian optimization-based framework of *combinatorial 3D shape generation*
- It creates a 3D shape with a set of *geometric primitives*.
- We also introduce a new *combinatorial 3D shape dataset* that consists of 14 classes and 406 instances.
- All the codes are available at `https://github.com/POSTECH-CVLab/Combinatorial-3D-Shape-Generation`.

Sequential Assembly with Unit Primitives

- Instead of employing other 3D representations such as point clouds, triangular meshes, and voxels, we create a sequence of unit primitives such as 2×4 LEGO bricks.

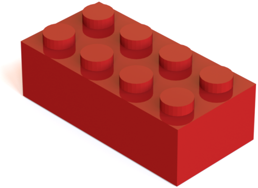


Figure 1: 2×4 LEGO brick.

- This 2×4 LEGO bricks make our problem more combinatorial and more complex, compared to other primitives.

Combinatorial 3D Shape Generation

- To determine the position of the next primitive, we define two evaluation functions regarding *occupiability* and *stability*.
- Occupiability encourages us to follow a target shape and stability helps to create a physically stable combination.
- We determine the position of the next primitive via *Bayesian optimization*.
- To avoid a suboptimal sequence, our framework includes a *rollback step*.

Experimental Results

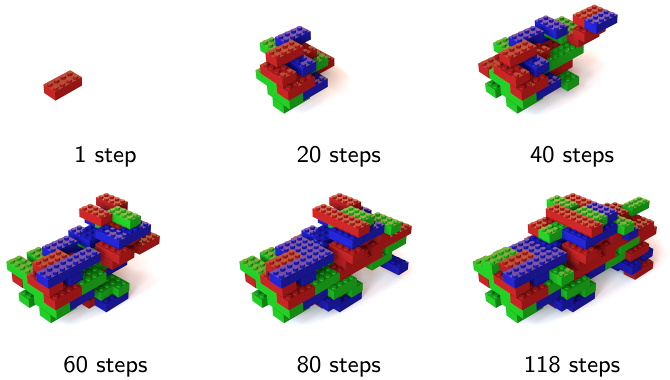
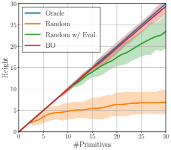


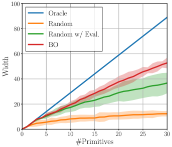
Figure 2: Generated assembling sequence that creates a *car* shape with 118 unit primitives.

Experimental Results

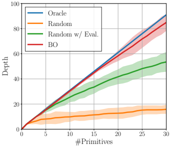
- We apply our framework in optimizing specific explicit functions.



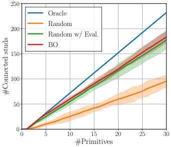
(a) Height



(b) Width



(c) Depth



(d) #Conn. studs

Figure 3: Quantitative results on maximizing explicit evaluation functions.

Combinatorial 3D Shape Dataset

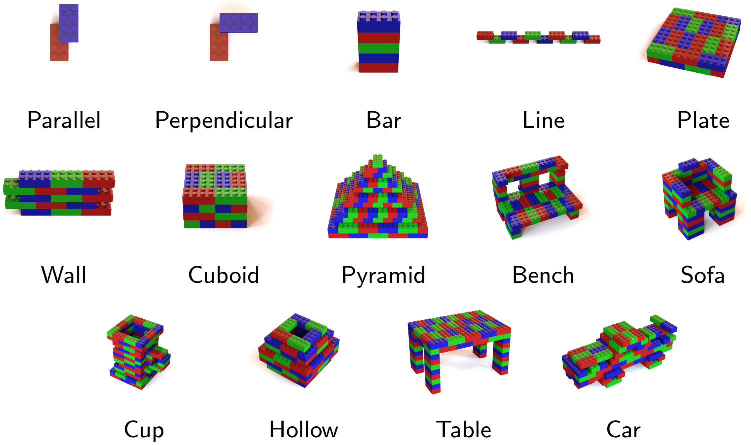


Figure 4: Selected examples from our dataset.

Combinatorial 3D Shape Dataset

- The characteristics of our combinatorial 3D shape dataset are
  1. *combinatorial*: Duplicates of unit primitive is repeatedly connected;
  2. *sequential*: Allowable connections between primitives are sequentially added;
  3. *decomposable*: By the combinatorial property, parts of combination can be sampled if they are valid in terms of the contact and overlap conditions;
  4. *manipulable*: New primitive is addable or the existing primitives are removable.

Conclusion

- We propose a sequential assembly method for a combinatorial 3D generation problem.
- It can generate a combinatorial shape, considering sample efficiency that is guided by Bayesian optimization.
- The evaluation function is based on global shape guidance and stability.
- We create a new dataset for combinatorial 3D models, which allows us to generate 3D shapes sequentially.

Thank you for watching our presentation.