Building LEGO Using Deep Generative Models of Graphs

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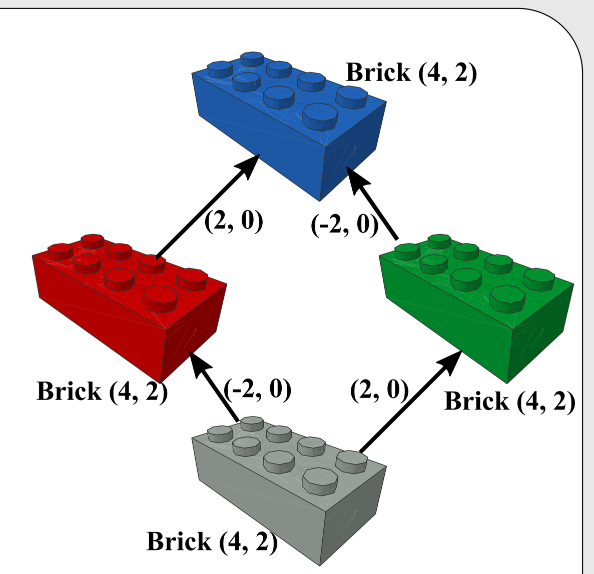
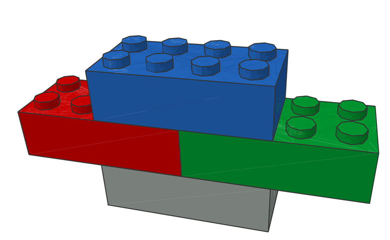
1. Motivation

- Recent significant advancement in generative models of text and images
- Less advancement in generative design
- Generative graph models are a great fit for the sequential assembly of LEGO

2. LEGO Graph Representation

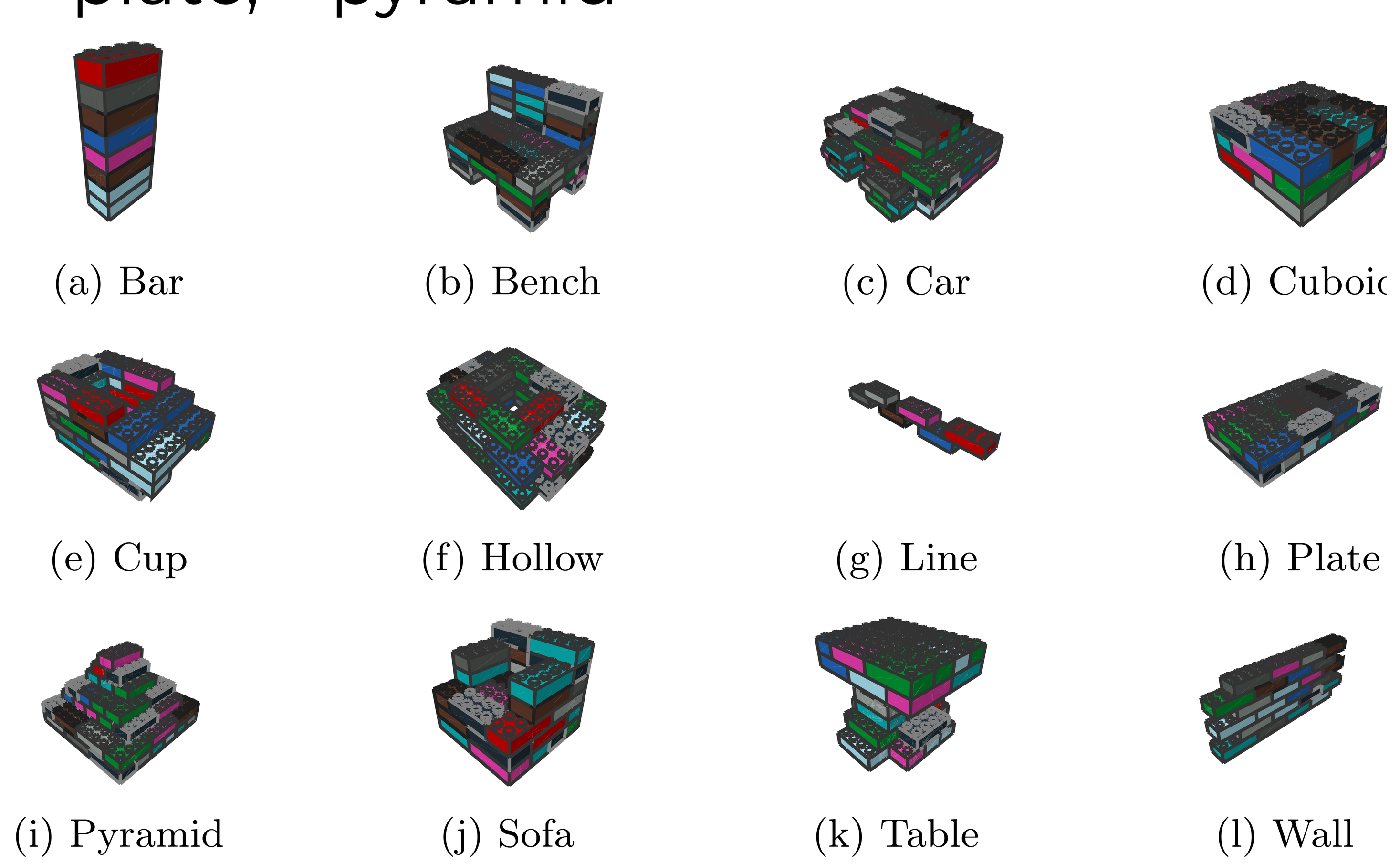
- Nodes represent LEGO bricks
- Node type determines brick orientation
- Edges indicate two bricks are connected
- Edge type contains connection information





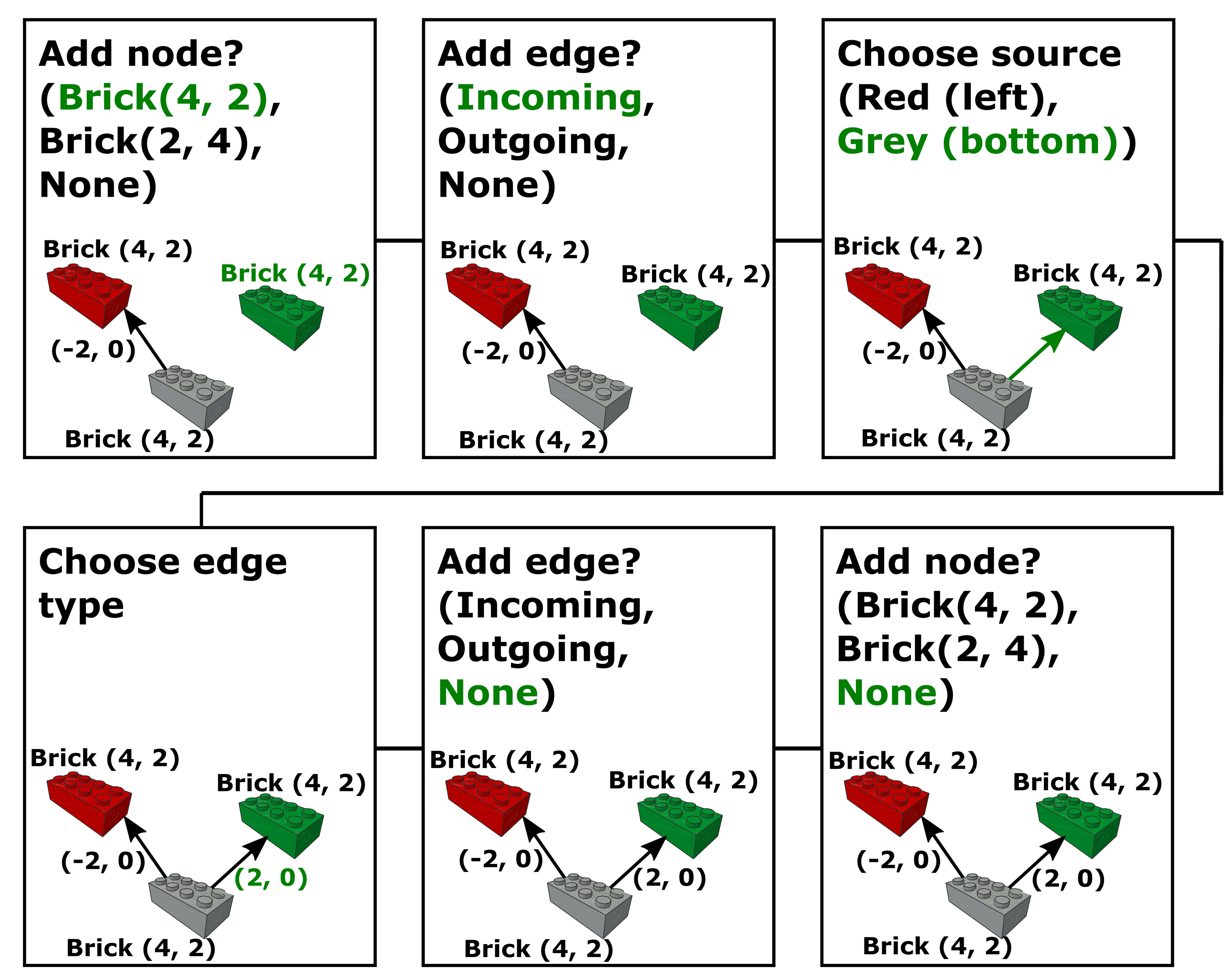
3. LEGO Dataset

- Consists only of 2x4 LEGO bricks
- 360 LEGO structures, 12 classes created by human subjects [1]
- Relatively simply shapes like “bench,” “plate,” “pyramid”



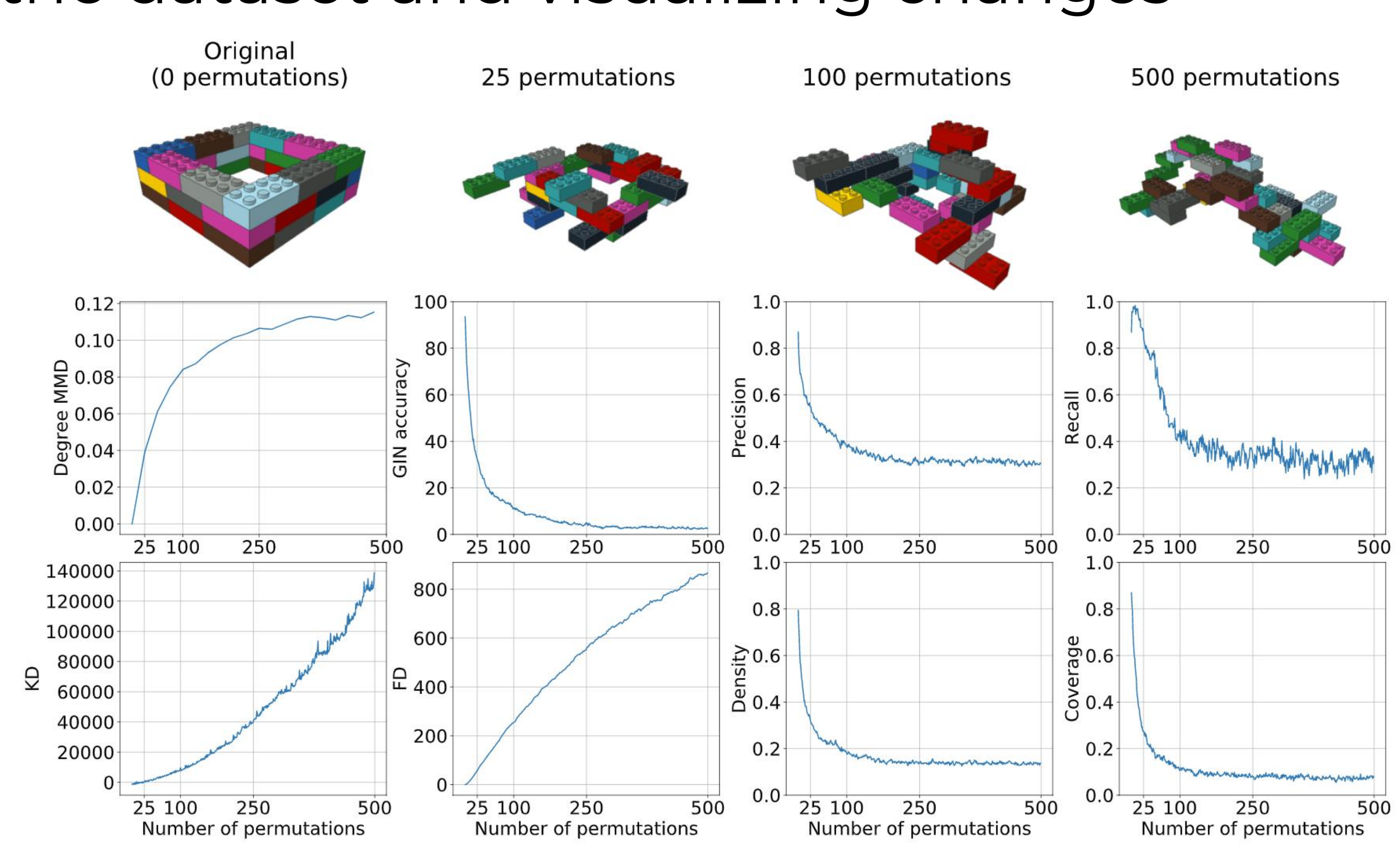
4. Graph Generative Model

- We expand the generative model DGMG by Li et al. [2] to handle LEGO graphs



5. Model Evaluation

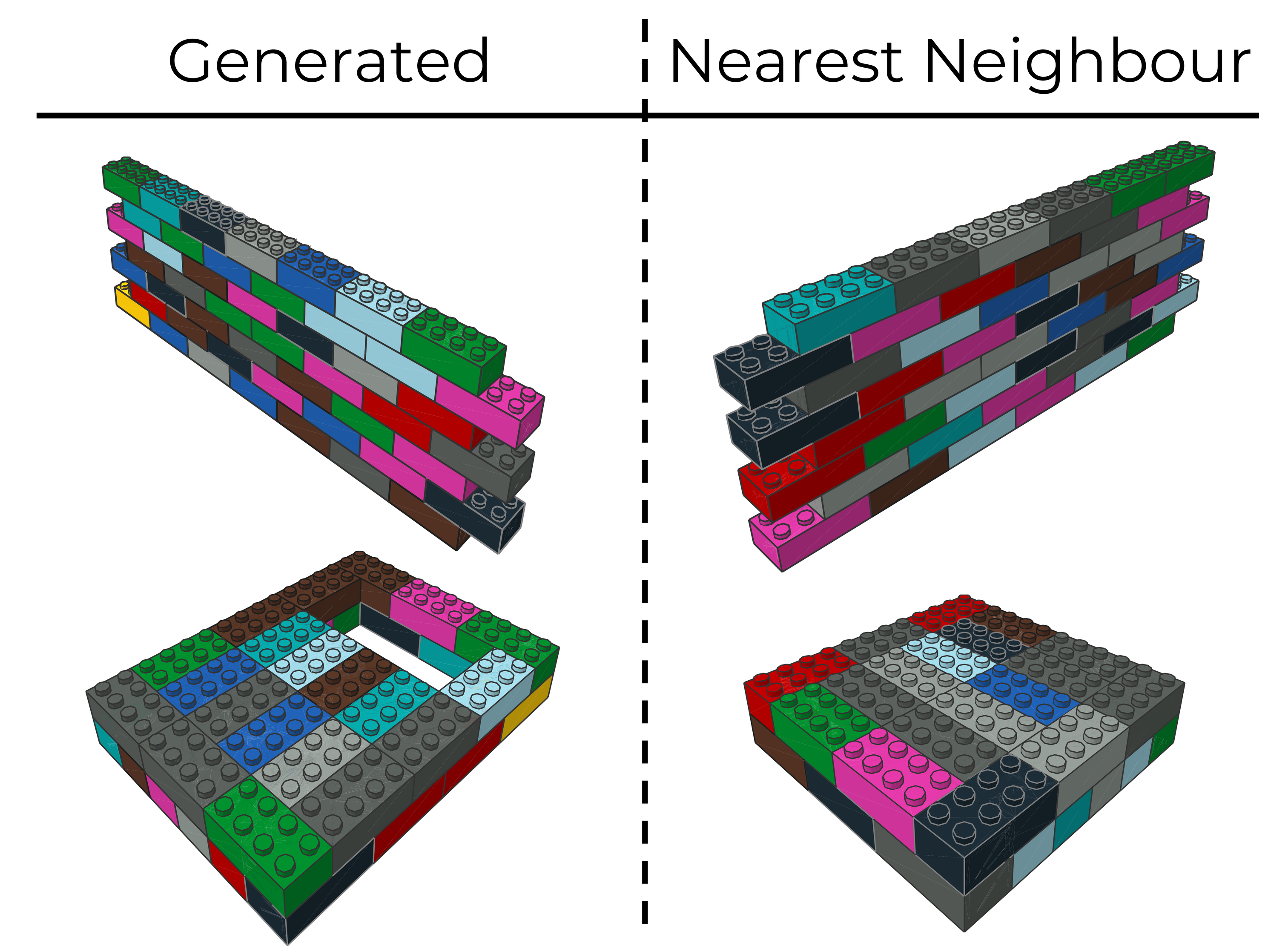
- We adapt several common metrics used in GANs to the graph domain
- We replace Inception v3 with a pre-trained graph classifier to obtain graph embeddings
- Validate the metrics by randomly permuting the dataset and visualizing changes



6. Results

Model	FID ↓	GIN Acc ↑	P ↑	R ↑	D ↑	C ↑
Ours	**150**	**60.5**	**0.62**	**0.92**	**0.48**	**0.23**
Bayes. Opt. [1]	345	24.5	0.47	0.70	0.23	0.078

- We generate significantly fewer valid structures: 25% vs. 100%
- Our model is able to replicate patterns in the dataset as seen below



7. Conclusion

- We demonstrated the effective use of graph generative models in physical design
- We showcase the value of adopting common GAN evaluation metrics to the generative graph domain

[1] Jungtaek Kim et al. “Combinatorial 3D Shape Generation via Sequential Assembly”. In: (Apr.2020). arXiv:2004.07414
[2] Yujia Li et al. “Learning Deep Generative Models of Graphs”. In International Conference on Learning Representations (ICLR) Workshop Track. 2018.