



We introduce HYGENE, a hierarchical diffusion-based method for hypergraph generation.

Motivation

- Hypergraphs (higher-order extension of graphs where hyperedges can contain more than two nodes) are more expressive than regular graphs.
- Broad field of application: 3D graphics (meshes), pharmaceutical research (molecules), electronics (circuit design).
- No method directly generates hypergraph and generating the incidence matrix as an image (using VAE, GAN and diffusion models) fails.
- Here we are interested in *unfeatured* hypergraphs. Our goal is to train a model able to sample a specific connectivity distribution.



Comparison of HYGENE with classical generation methods

Generated examples



Train

Generated

Train

(b) Stochastic Block Model

Numerical Results

(a) Erdos-Renyi

Model	SBM Hypergraphs ($n_{avg} = 31.73$, $std = 0.55$)				Ego Hypergraphs ($n_{avg} = 109.71, std = 10.23$)			
	Valid SBM ↑	Node Deg ↓	Edge Size ↓	Spectral \downarrow	Valid Ego ↑	Node Deg ↓	Edge Size ↓	Spectral \downarrow
HyperPA	2.5%	4.062	0.407	0.273	0%	2.590	0.423	0.237
VAE	0%	1.280	1.059	0.024	0%	0.803	1.458	0.133
GAN	0%	2.106	1.203	0.059	0%	0.917	1.665	0.230
Diffusion	0%	1.717	1.390	0.031	0%	3.984	2.985	0.190
HYGENE	65%	0.161	0.002	0.010	90%	0.063	0.220	0.004

[1] Bergmeister, A., Martinkus, K., Perraudin, N., Wattenhofer, R. (2023). *Efficient and scalable graph generation through iterative local expansion* [2] Loukas, A. (2019). Graph reduction with spectral and cut guarantees Acknowledgments: The authors acknowledge the ANR – France (French National Research Agency) for its financial support of the System On Chip Design leveraging Artificial Intelligence (SODA) project under grant ANR-23-IAS3-0004 and the JCJC project DeSNAP ANR-24-CE23-1895-01. This project has also been partially funded by the Hi!PARIS Center on Data Analytics and Artificial Intelligence.

HYGENE: A Diffusion-based Hypergraph Generation Method

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Like graphs [1], unzoom (lose details) and train a model to zoom (reconstruct details). Working on graph projections is easier than on hypergraphs.

Generated

(c) Ego

Tree Hypergraphs **Erdos-Renyi Hypergraphs** ModelNet40 Pia $(n_{avg}=$ 32, std= 0) $(n_{avg} = 32, std = 0.07)$ $(n_{avg} = 177.29, std = 0.07)$ ∧ Node Edge Spectral ↓ Node Edge Valid Node Edge Spectral \downarrow Spec $\mathsf{Deg} \downarrow \mathsf{Size} \downarrow$ Tree \uparrow Deg \downarrow Size \downarrow $\mathsf{Deg} \downarrow \mathsf{Size} \downarrow$ 0.315 0.284 5.530 0.183 9.254 **0.023** 0.159 0.177 0% 0.072 0.480 0.124 2.140 0.540 0.035 8.060 1.686 0.469 2.560 0.657 409.0 86.38 0.151 0.089 0.048 0. 1.718 1.922 0.127 2.225 0.781 20.90 4.192 0.014 77.5% 0.059 0.108 **6.290** 0.027 0.012 0.445 0.012 0.006 0

Ideas

- Maintained in parallel during coarsening.



(a) Original hypergraph

A hypergraph and its clique and star expansions

Train

Generated

(d) Tree

no = 57.11)	ModelNet40 Plant $(n_{avg} = 124.86, std = 87.88)$					
ctral ↓	Node Deg ↓	Edge Size ↓	Spectral ↓			
067	6.566	0.046	0.061			
396	3.895	1.573	0.205			
697	378.1	56.35	0.364			
113	21.03	3.439	0.069			
117	2.428	0.027	0.034			

Train

Generated

(e) ModelNet40 Plant meshes

Conclusions

- ation.
- ing processes [2] to hypergraphs.
- capability to generate hypergraphs from targeted distributions.

Next: Add features. Currently working on mesh generation.



Clique expansion: Each hyperedge is collapsed into a clique. The clique expansion has the same spectral properties as its hypergraph, but recovering a hypergraph from its clique expansion is *NP-hard*. Used for coarsening.

2. Star expansion: The hypergraph is turned into a bipartite graph, where left side nodes correspond to the original nodes, and right side nodes to hyperedges. Each hyperedge is then connected to all of its nodes. Very easy to manipulate.





(c) Star expansion

(b) Clique expansion

(f) ModelNet40 Piano meshes

• We introduced HYGENE, the first diffusion-based approach for hypergraph gener-

• Our work generalizes previous iterative local expansion schemes [1] and coarsen-

• By training a denoising diffusion model, we successfully validated the method's