GraSPy: an Open Source Python Package for Statistical Connectomics Benjamin D. Pedigo<sup>1</sup>, Jaewon Chung<sup>1</sup>, Eric W. Bridgeford<sup>2</sup>, Bijan Varjavand<sup>3</sup>, Carey E. Priebe<sup>3</sup>, Joshua T. Vogelstein<sup>1</sup> <sup>1</sup>Department of Biomedical Engineering, Johns Hopkins University <sup>2</sup>Department of Applied Mathematics and Statistics, Johns Hopkins University

		Su	ummary			
<ul> <li>Connectome datasets are growing in size</li> <li>Analysis is a current bottleneck</li> </ul>		<ul> <li>Graphs (networks) are natural models</li> <li>GraS</li> <li>Require specific statistical tools and implementer</li> <li>Graphic data of the statistical tools and implementer</li> </ul>	<b>SPy</b> : open source python toolkit [2] oh sampling, estimation, embedding, testing	<ul> <li>Accelerate understate valid graph inference</li> <li>Available at neurod</li> </ul>		
		Graphs		Graph embe	eddings	
$6 \\ 4 \\ 5 \\ (1)$	$\begin{pmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 \end{pmatrix}$	• Model adjacency matrices as samples from a matrix of probabilities $P$ : $A \sim Bernoulli(P)  P \in \mathbb{R}^{n \times n}$	<ul> <li>Embeddings convert graphs representations, allowing s ference and estimation</li> </ul>		lension 2	Type pharynx nonpharynx linker
3-2 Jundiroctod graph	$ \begin{pmatrix} 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix} $	<ul> <li>Latent position random graphs: latent vector for each node de- termining probability of connections</li> </ul>	<ul> <li>Multigraph embeddings car</li> <li>lation of graphs in the same</li> </ul>			80000 00 V-

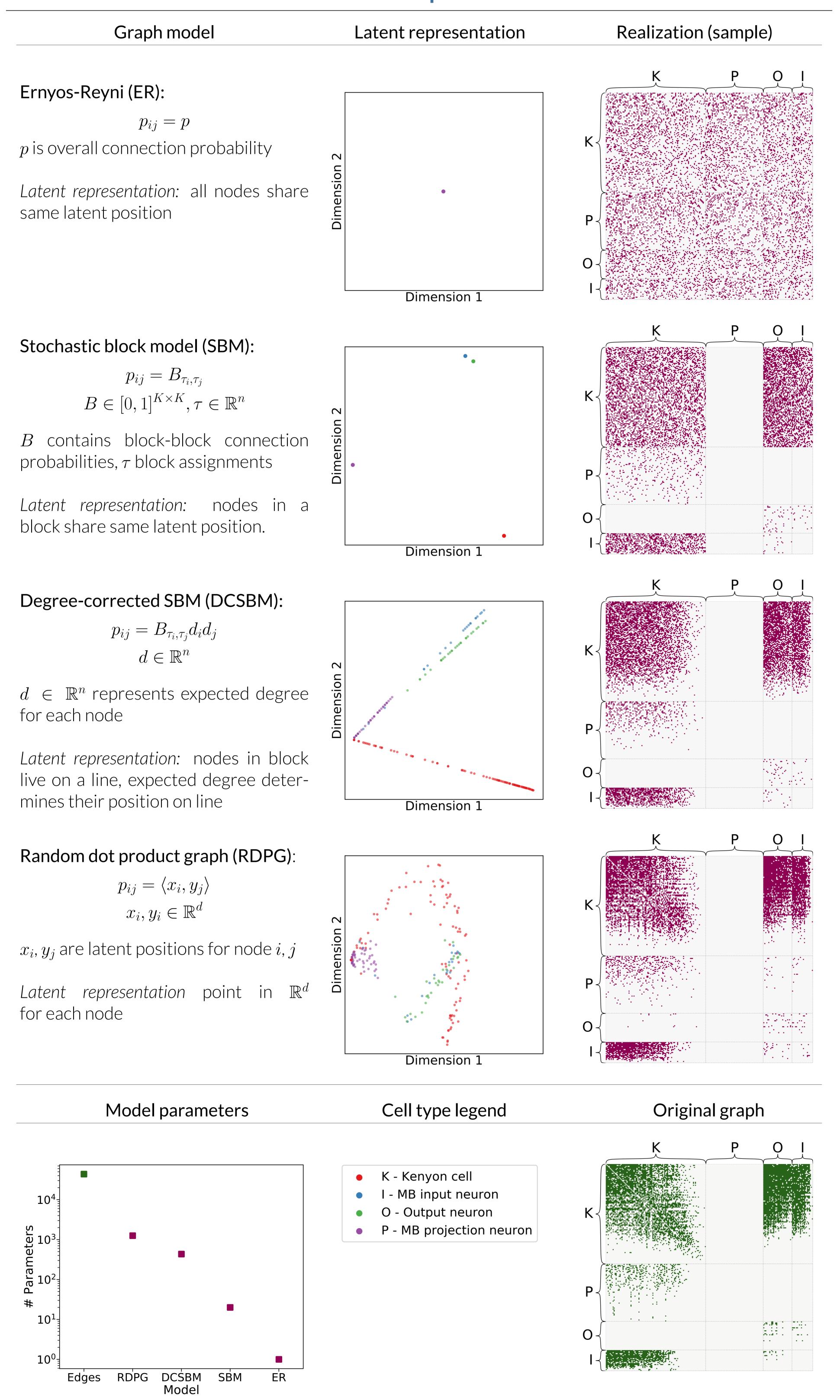
Undirected graph Adjacency matrix Atermining probability of connections

• Find P using the dot product of the latent positions

 $P = XX^T, \quad X \in \mathbb{R}^{n \times d}$ 

where row i of X is a latent vector for node j [1]

# **Random Graph Models**



sions

 $\overline{\Box}$ 

Embeddings such as adjacency spectral embedding (ASE) can be generative models for random graphs (Figure 1).

#### **Dimension** 1

Figure 2. Laplacian spectral embedding (LSE) on the hermaphrodite C. elegans connectome [3], showing pharynx/nonpharynx division

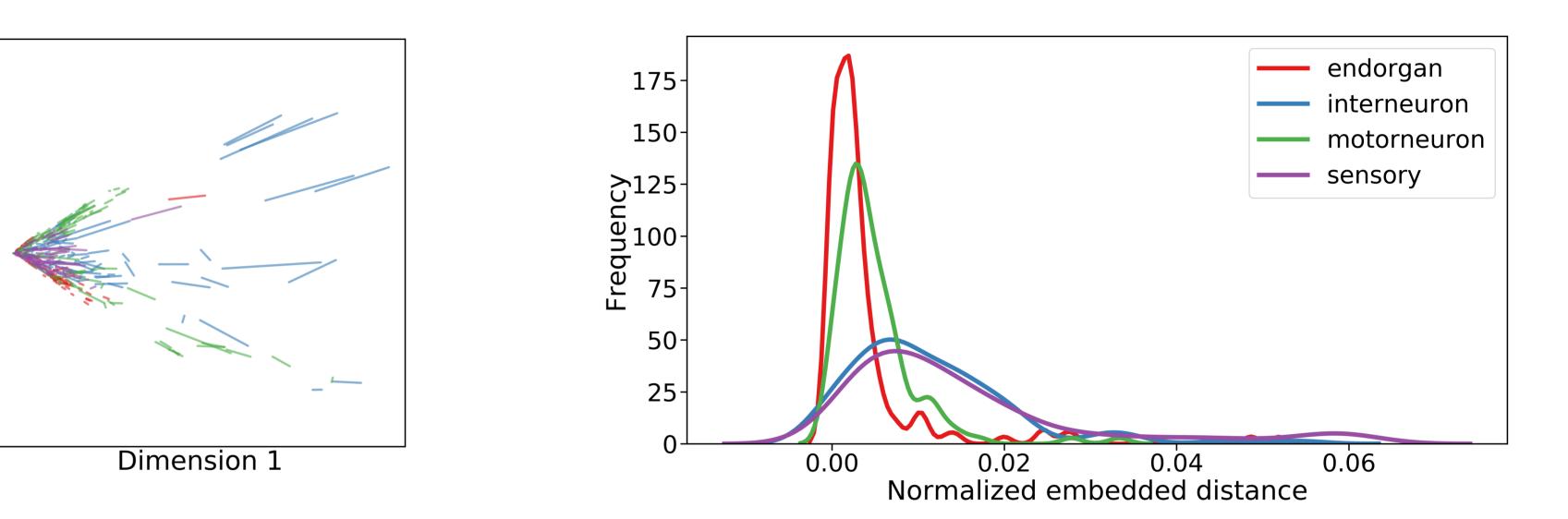


Figure 3. Omnibus embedding of the male and hermaphrodite C. elegans connectome, lines show disparity between sex for each node

Figure 4. Kernel density estimates (KDEs) of distances in the embedding plotted by cell type, color coded as in Figure 3

# Graph hypothesis testing

How to test if two graphs ( $G_1$ and $G_2$ ) were gen-	
erated from same distribution?	

Graphs	Adjacen Embedo			
	$egin{bmatrix} y_{1,1} & y_{1,2} \end{pmatrix}$			

Two-Sample ncy Spectral dding (ASE) **Semiparametric Test** 

 $\cdots y_{1,d}$ 

# $G_1 \sim P_1, G_2 \sim P_2$ $H_0: P_1 = P_2, \quad H_a: P_1 \neq P_2$

- GraSPy implements two such hypothesis tests
- Matched test: correspondence between node identities is known
- Unmatched test: correspondence between nodes is unknown or does not exist

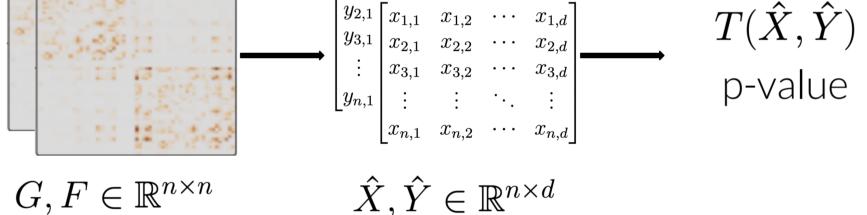
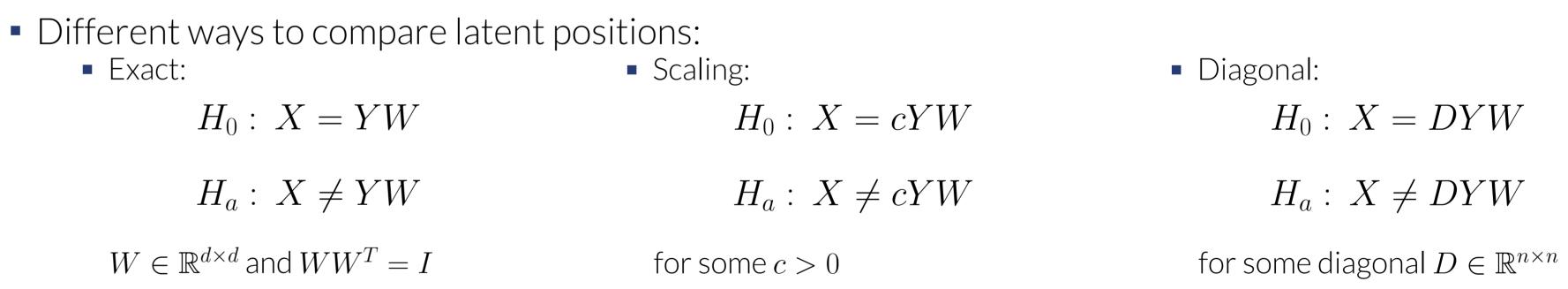


Figure 5. Procedure for the matched test of Tang et al. [5]. Two graphs are embedded using ASE, embeddings are aligned, test statistic is computed as distance between the aligned embeddings.



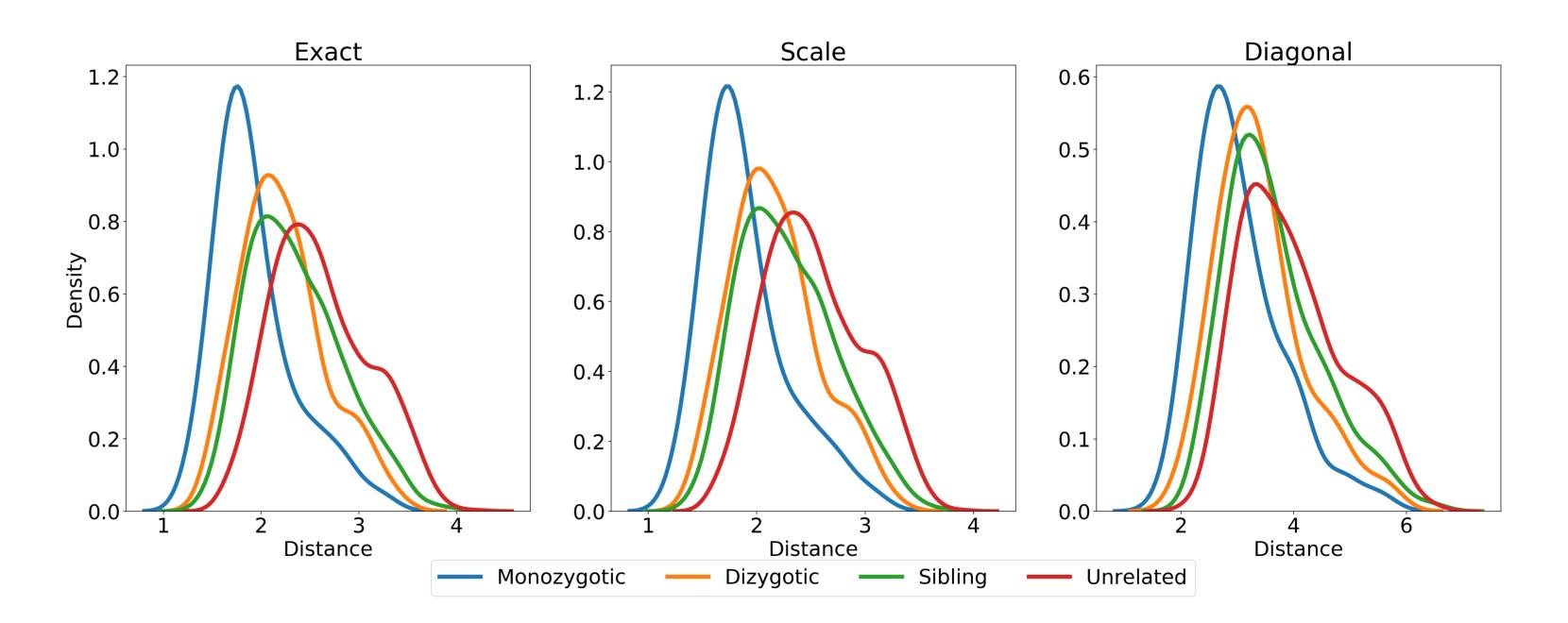


Figure 1. Four random graph models displayed with their corresponding representations in latent space and a sample from the graph model. All graph models are fit to the *Drosophila* left mushroom body from Eichner et al [4]. The latent space representations are calculated by computing an adjacency spectral embedding of the estimated probability matrix from each model.

Figure 6. KDEs of matched test statistics for dMRI connectomes from Human Connectome Project Young Adult study [6], compared for different levels of relatedness

### Conclusion

- GraSPy provides tools for graph hypothesis testing and estimation
- Tools will allow neuroscientists to make claims about graph-value data
- GraSPy will continue to grow and add functionality in particular, we aim to consider node and edge attributes

## References

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