Generative kernel embedding for weighted directed networks

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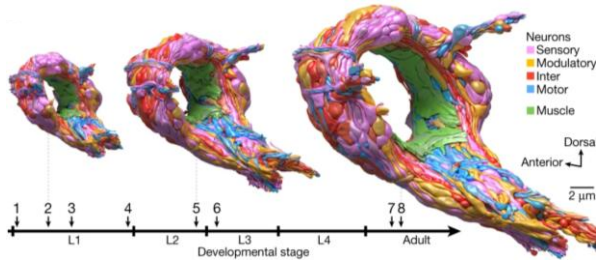
Context : Real connectome instances

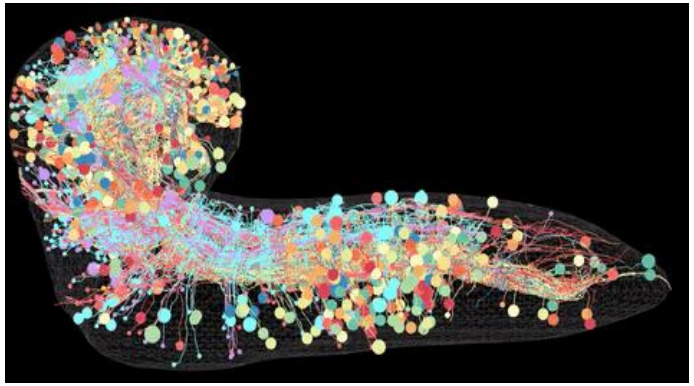
Full connectome instances at synaptic resolution

C. elegans connectome



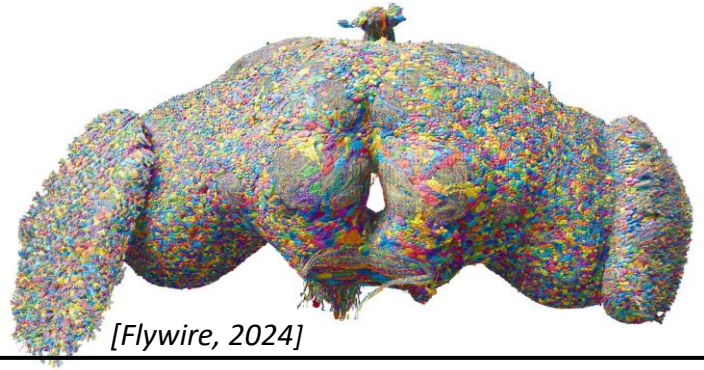
[Witvliet et al, Nature 2021]

Drosophila larva central nervous system



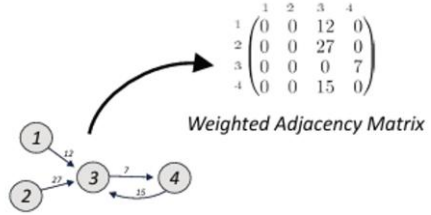
[Winding et al, science 2023]

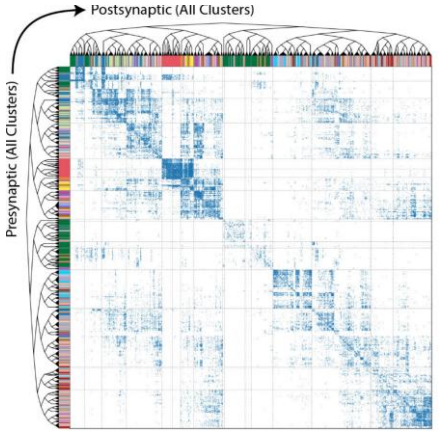
Drosophila adult brain



[Flywire, 2024]

Connectome representation





Graph with weighted adjacency matrix :

$$\hat{w}_{i,j}$$

nb synapses from i to j

Dimensions : nb of neurons n

Memory size : $O(n^2)$

Objective & **Approach**: Latent space embedding

How to have a better representation with weighted directed graph ?

Latent space graph embedding

Memory size : $O(nd),\ d \ll n$

Desired properties of the approach:

- Low dimensional
- Generative
- Latent space properties
- Looking for structures and circuits

$$\mathcal{L} = - \sum_{x_i \in \text{Pre-n}, y_j \in \text{Post-n}} \underbrace{\ln\left(\mathbb{P}(w_{i,j} = \hat{w}_{i,j} | k(x_i, y_j))\right)}_{\text{Log likelihood}}$$

$$\mathbb{P}\left(w_{i,j} = \hat{w}_{i,j} | k(x_i, y_j)\right)$$

→ Poisson law

parametrized by $\lambda = k(x_i, y_j)$