



# GSP ON THE DIGITAL RECONSTRUCTION OF THE BRAIN

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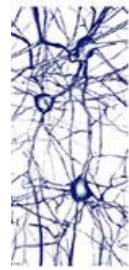
Stefania Ebli - Christopher Elin - Florian Roth

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NTDS Project 2017/18

- Data Exploration
- Network Analysis
- Clusters
- Layers Prediction





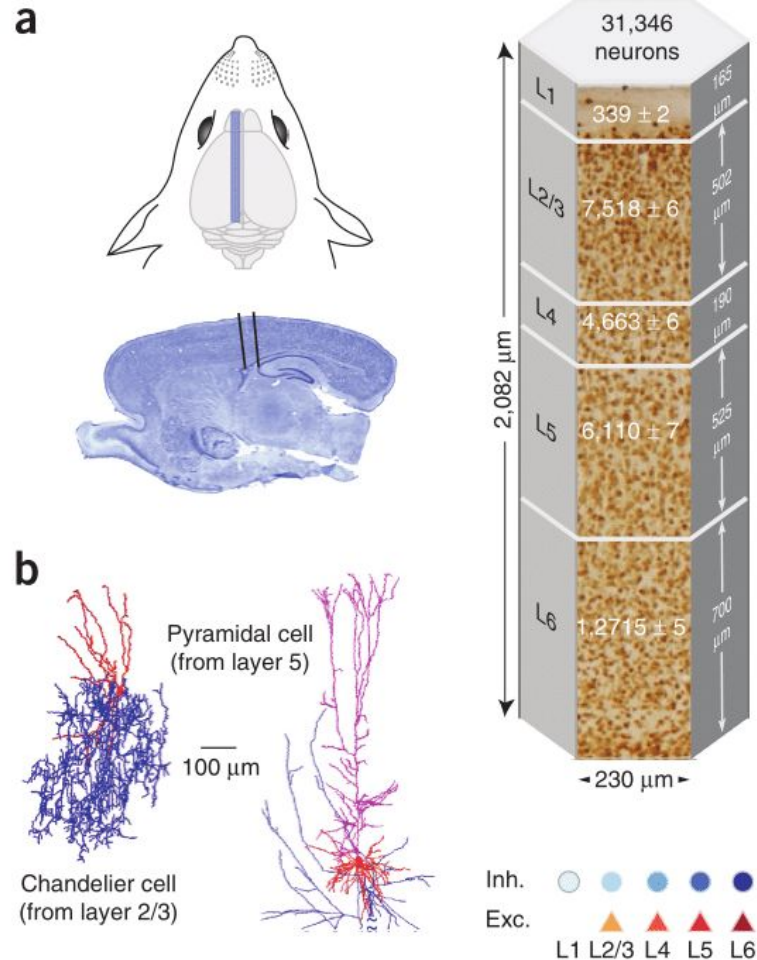
# Blue Brain Project

## Digital Reconstruction of Neocortical Microcircuitry:

- Biologically consistent
- Reproduce anatomy and physiology

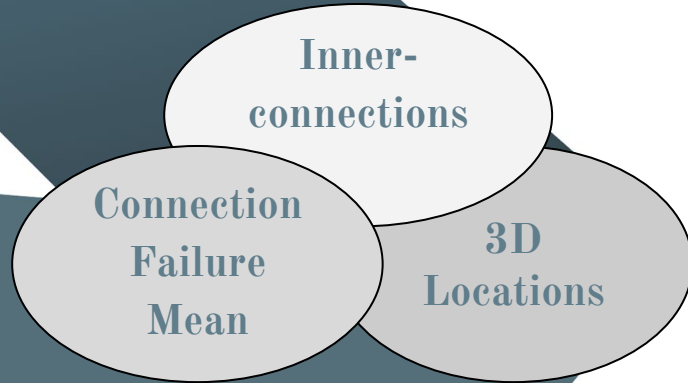
## Modeled subunits/microcolumns:

- ~31000 neurons
- ~7.8 million connections
- 6 layers

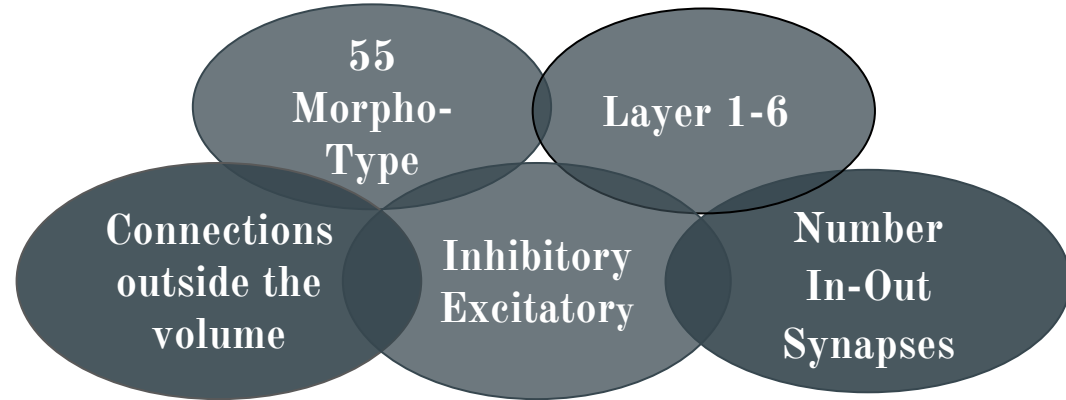


# Data available for each Neuron:

(The Neocortical Microcircuit Collaboration Portal)



Connectivity Matrix: 31346 nodes,  $p=0.015\%$   
&  
Weights

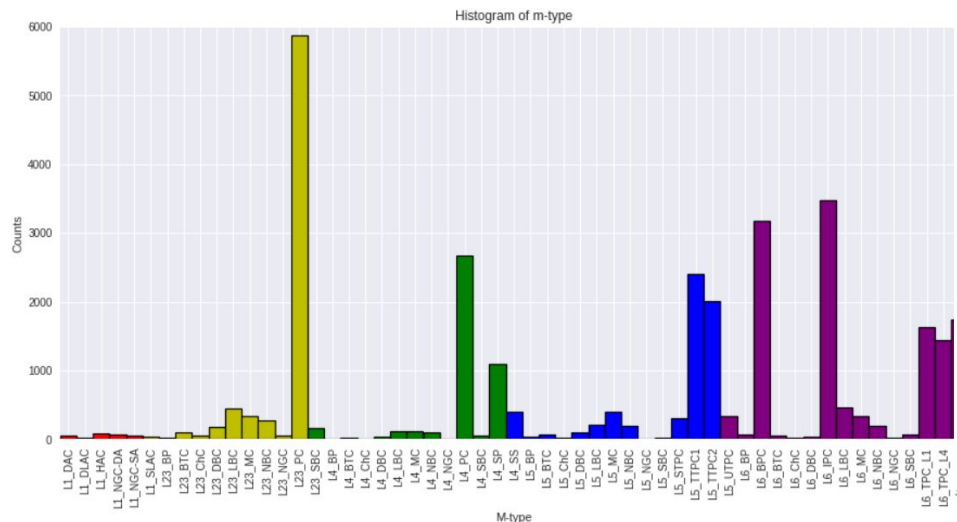


Statistical Analysis  
&  
Labels

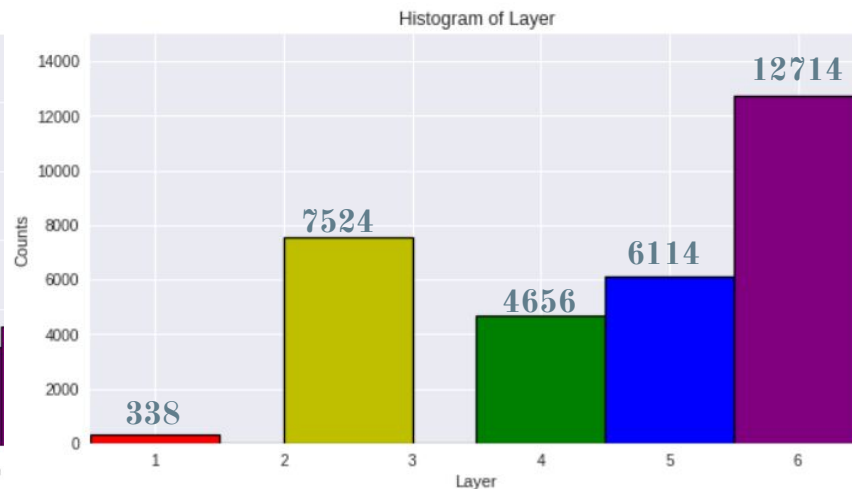
# Network properties

- Original graph is directed

Histogram of the 55 morphological types:



Histogram of the 6 layers:



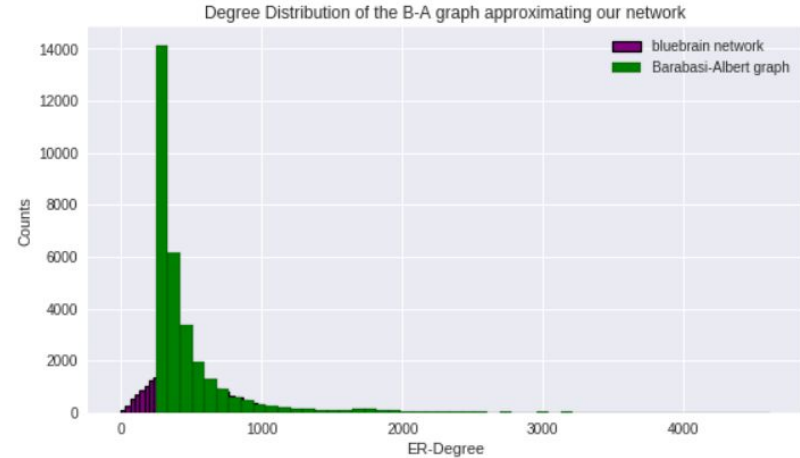
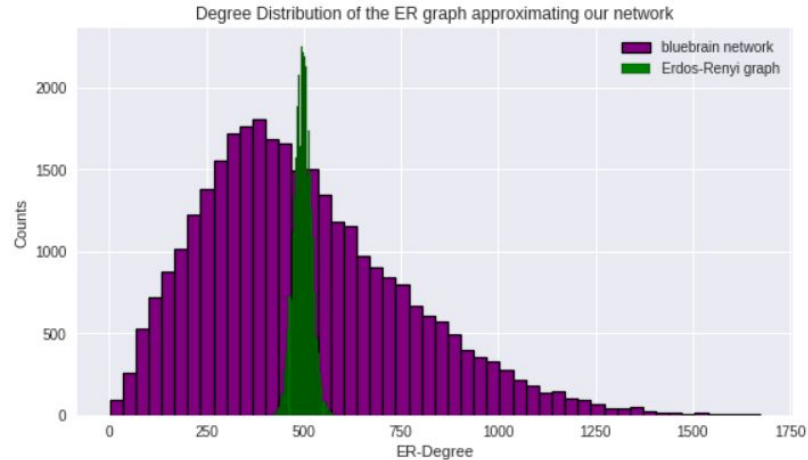
Hubs: different m-types are typically hubs for the out-degree (L4\_PC) and the in-degree (L5\_TTCP)

# Network models

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Can our network be approximated by an Erdős–Rényi or a Barabasi-Albert network?

→ Create networks with same amount of nodes and connection probability



Degree distribution of our network is widely distributed but not by a power law

→ Degree distribution can not be modeled by either of the networks

# Network models properties

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Network	Average path length	Diameter	Clustering Coefficient
BlueBrain network directed	2.48	-	-
BlueBrain network undirected	2.33	5	0.057
Erdős-Rényi-Graph	1.98	3	0.016
Barabási-Albert-Graph	1.99	3	0.048

➤ small world property ✓

➤ Clustering coefficient ✗

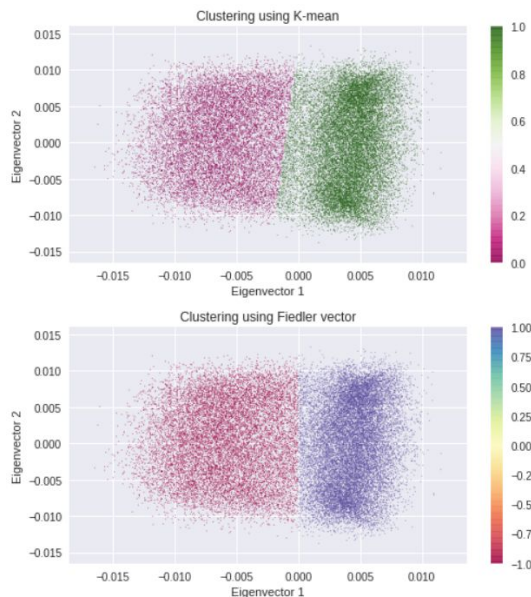


# Spectral Clustering

- Goal: can spectral clustering classify neurons by biological or structural properties?
- Matrices: unweighted connectivity matrix and weighted connectivity matrix (failure rates)

Embedding using Laplacian eigenmaps of the Unweighted and Weighted Normalized Laplacian

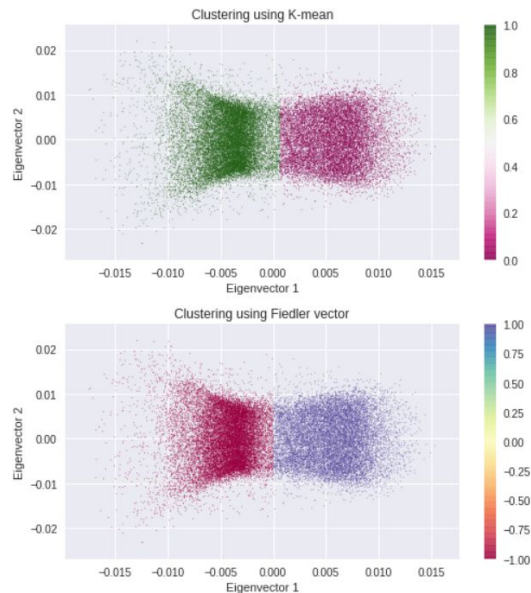
unweighted



k-mean ( $k = 2$ )

sign Fiedler vector

weighted

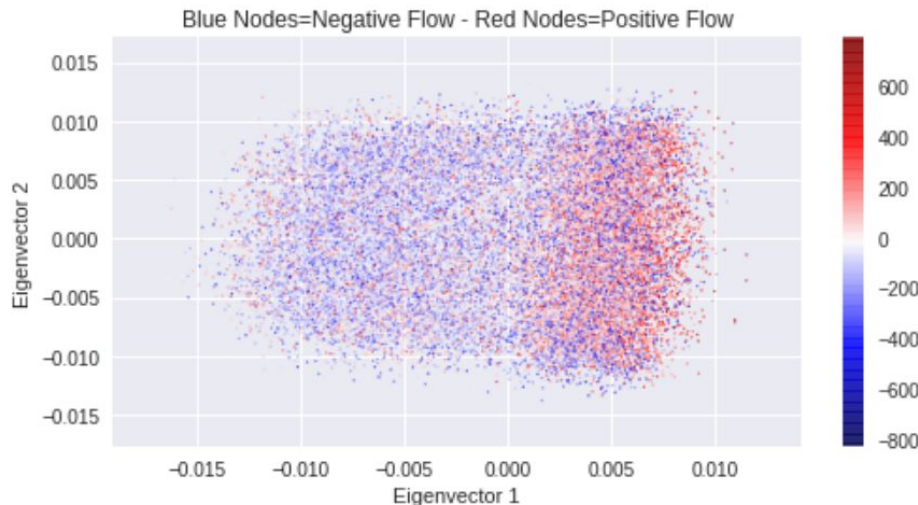




# Signal-flow based Clustering

- Goal: how strongly the signal flows through every node (processing depth) is correlated with the 1st or 2nd eigenvector?
- Inspiration: embedding of the C. elegans network [1] using Laplacian eigenmaps
- Labels: Total Flow = Out-Degree - In-Degree
- Classifier: sign of the Fiedler vector

Embedding using Laplacian eigenmaps of the Unweighted Normalized Laplacian

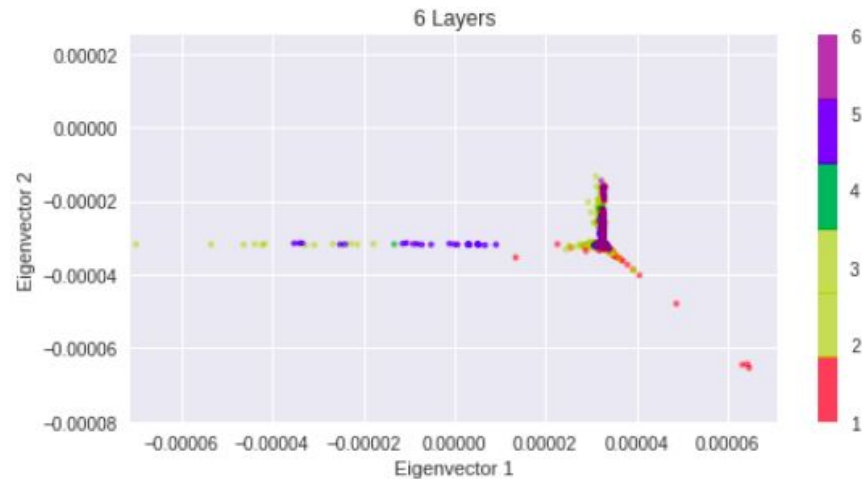
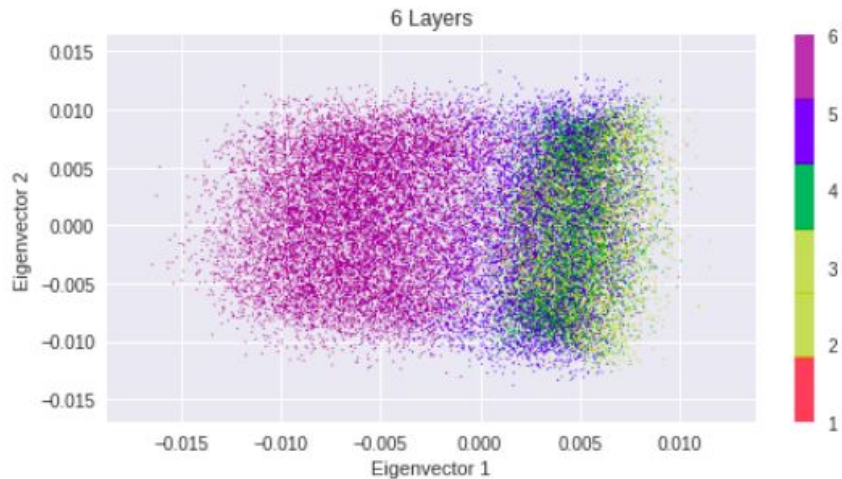


- Obtained accuracy when predicting the sign of the Total Flow:  
68.44%

# Layers-based clustering

- Goal: are the 1st or 2nd eigenvectors related to the position of the neurons layers 1-6?
- Labels: Layer 1-5 and Layer 6
- Classifier: sign of the Fiedler vector

Embedding using Laplacian eigenmaps of the :  
Unweighted Normalized Laplacian      Unweighted Combinatorial Laplacian

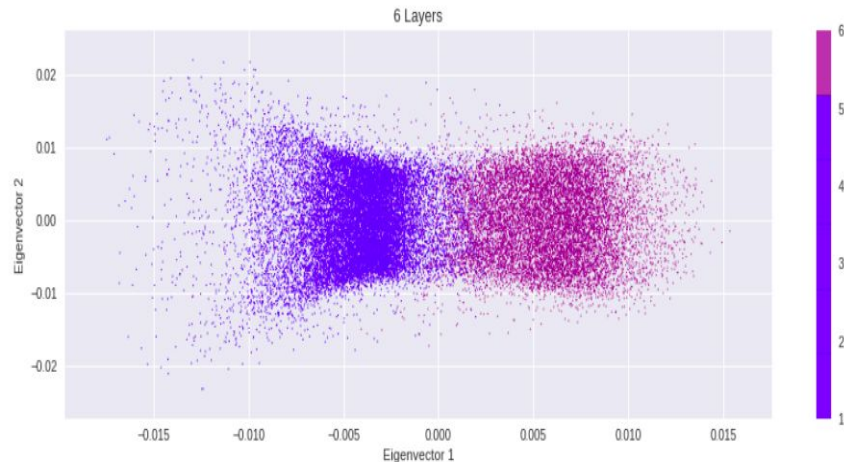
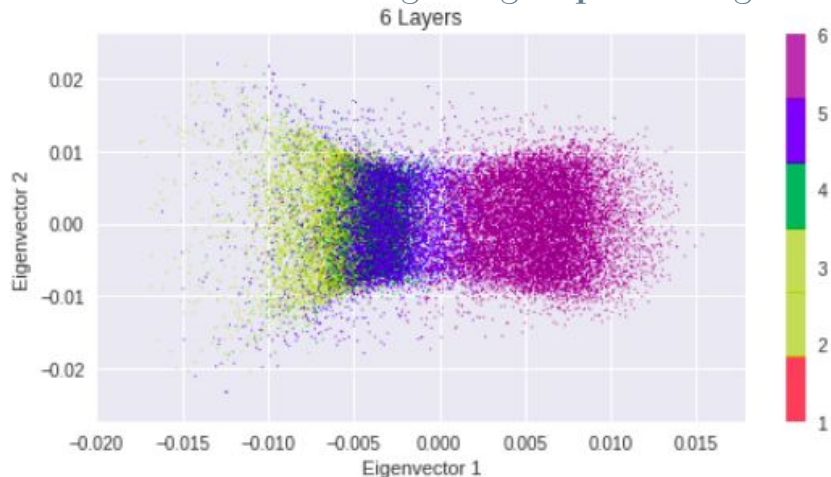


- Sign of the Fiedler vector of the normalized laplacian separates layer 6 from all other layers!
- It separates layer 6 from all other layer with an accuracy of 94.76%

# Layers-based clustering: weighted connectivity matrix

- Weights: failure mean
- Labels: Layer 1-5 and Layer 6
- Classifier: sign of the Fiedler vector

Embedding using Laplacian eigenmaps of the Weighted Normalized Laplacian



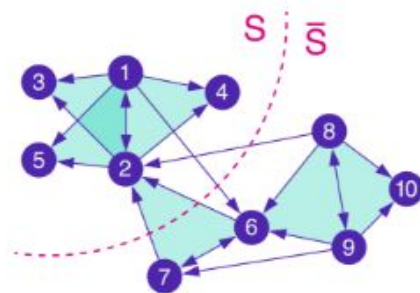
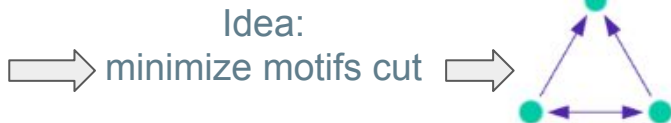
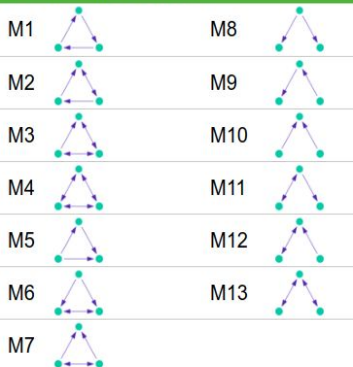
- The Fiedler vector of the normalized Laplacian is a spatial separator: it distinguishes 3 layers!
- The sign of the Fiedler vector separates layer 6 from all other layers with an accuracy of 96.58%

# Motif-based clustering

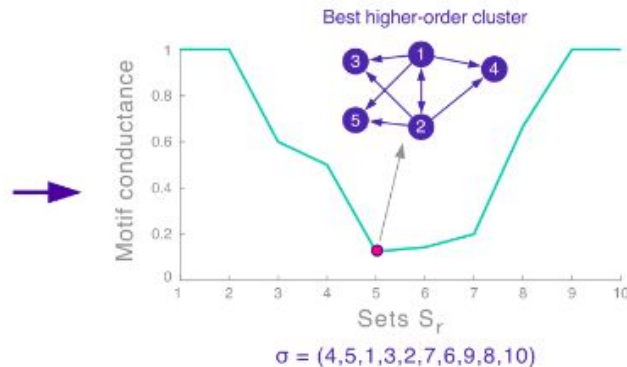
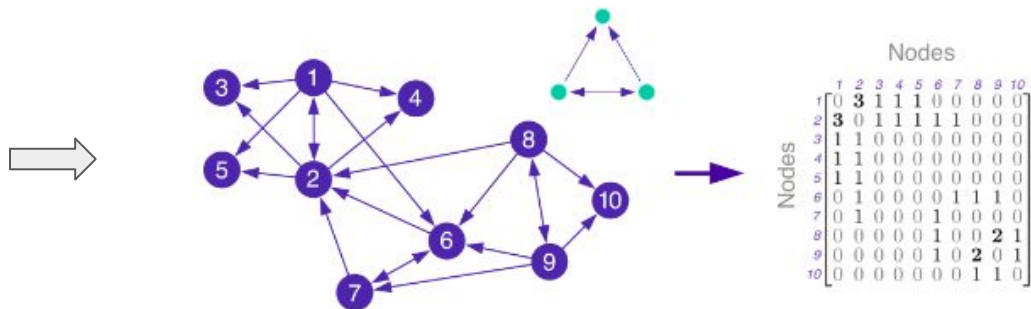
Motivation: taking into account the direction of signal flow

## 1. Choose motif

Motif naming conventions



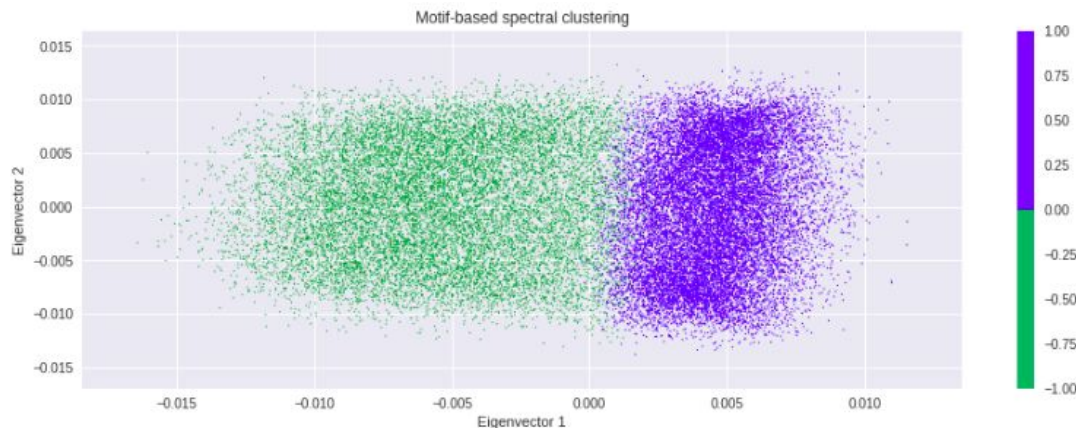
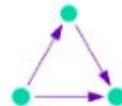
$$\phi_M(S) = \frac{\text{motifs cut}}{\min(8, 10)} = \frac{1}{8}$$



# Motif-based clustering on the connectivity matrix

1. Choose the most recurrent motif in the microcircuit network:
2. Compute the 2 cluster given by the motif-based spectral clustering algorithm.

M5



- Accuracy in distinguish neurons in layer 6: 94.06%
- Similar clustering as the sign of the Fiedler vector

# Prediction of layers

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- Goal: Predict if a neuron is in layer 6 just knowing the connectivity matrix.
- How: revisited linear regression with ‘smoothness of signal’ on the graph

$$\mathbf{x}^* = \arg \min_{\mathbf{x} \in \mathbb{R}^N} \|\mathbf{y} - \mathbf{M}\mathbf{x}\|_2^2 + \alpha \mathbf{x}^\top \mathbf{L} \mathbf{x}$$

$$(\mathbf{M}^2 + \alpha \mathbf{L}) \mathbf{x}^* = \mathbf{M} \mathbf{y}$$

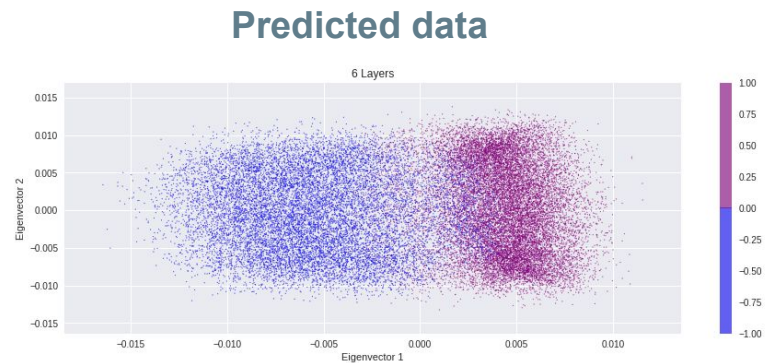
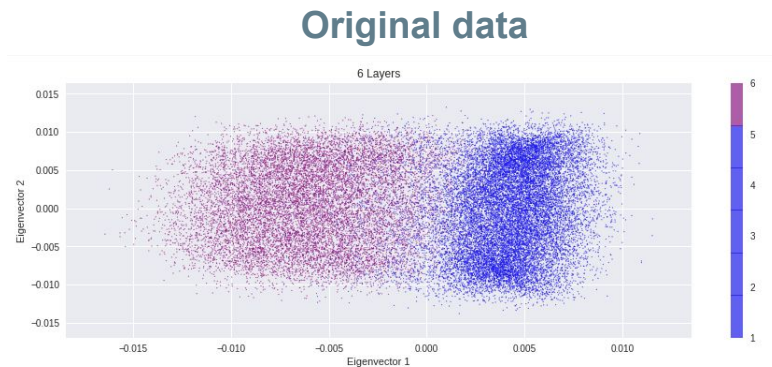
- $\alpha$  is an hyper-parameter which controls the trade-off between the data fidelity term and the smoothness prior



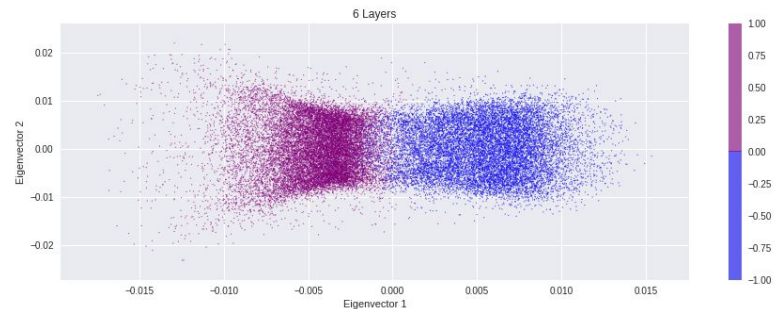
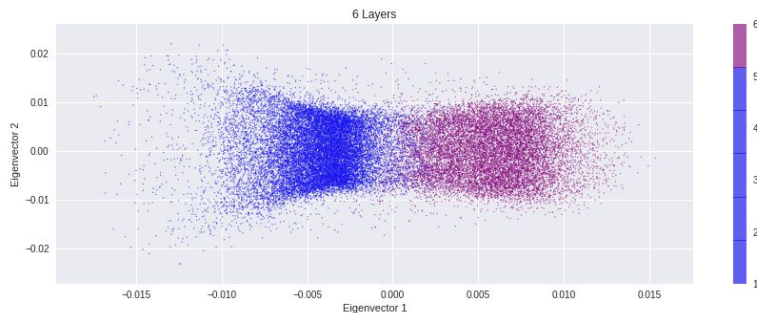
# Prediction : visualization

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Unweighted



Weighted



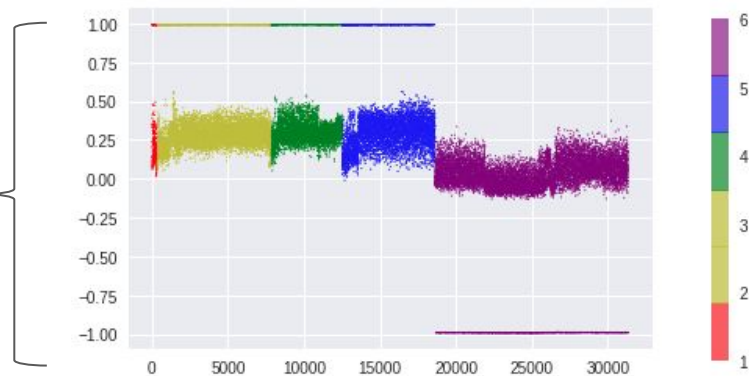


# Prediction : performances

- $\alpha = 0.01$
- Keeping **10%** of the original data

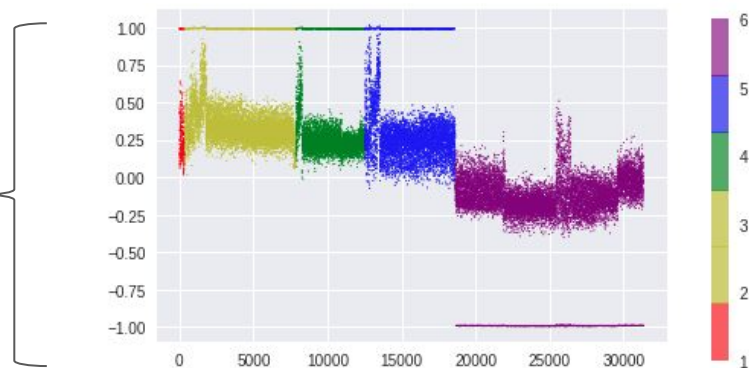
Unweighted : We can predict if a neuron is in the 6th layer, or not, with an error equal to : **7.55%**

Unweighted



Weighted : **4.72%** of errors

Weighted



# Prediction : influence of the parameters

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**Unweighted** connectivity matrix | **Weighted** connectivity matrix

p	$\alpha = 0.01$	$\alpha = 0.1$	$\alpha = 1$
0.05	15.6   8.05	16.7   8.60	25.7   14.6
0.1	7.55   4.72	8.04   4.86	12.7   6.41
0.2	4.93   3.68	7.55   3.69	6.95   4.24
0.5	2.59   2.31	2.62   2.29	2.89   2.24

Error rates

- $\alpha$  decreases -----> error **decreases**
- p decreases -----> error **increases**

# Conclusion

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1. **Caveats:** It is hard to interpret very complex biological data
2. **Results:** It is possible to distinguish layer 6 from all the others only by knowing the connectivity matrix
3. **Future directions:** excitatory-inhibitory predictions by changing the matrix weights, using as a signal the voltage coming from simulations.

Thank you for your attention!

# References

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- [1] <http://www.wormatlas.org/neuronalwiring.html#CelegansNeuralNetwork>
- [2] [Motif-based spectral clustering](#) SNAP, Stanford.
- [3] [Reconstruction and Simulation of Neocortical Microcircuitry](#) (Markram et al., Cell)