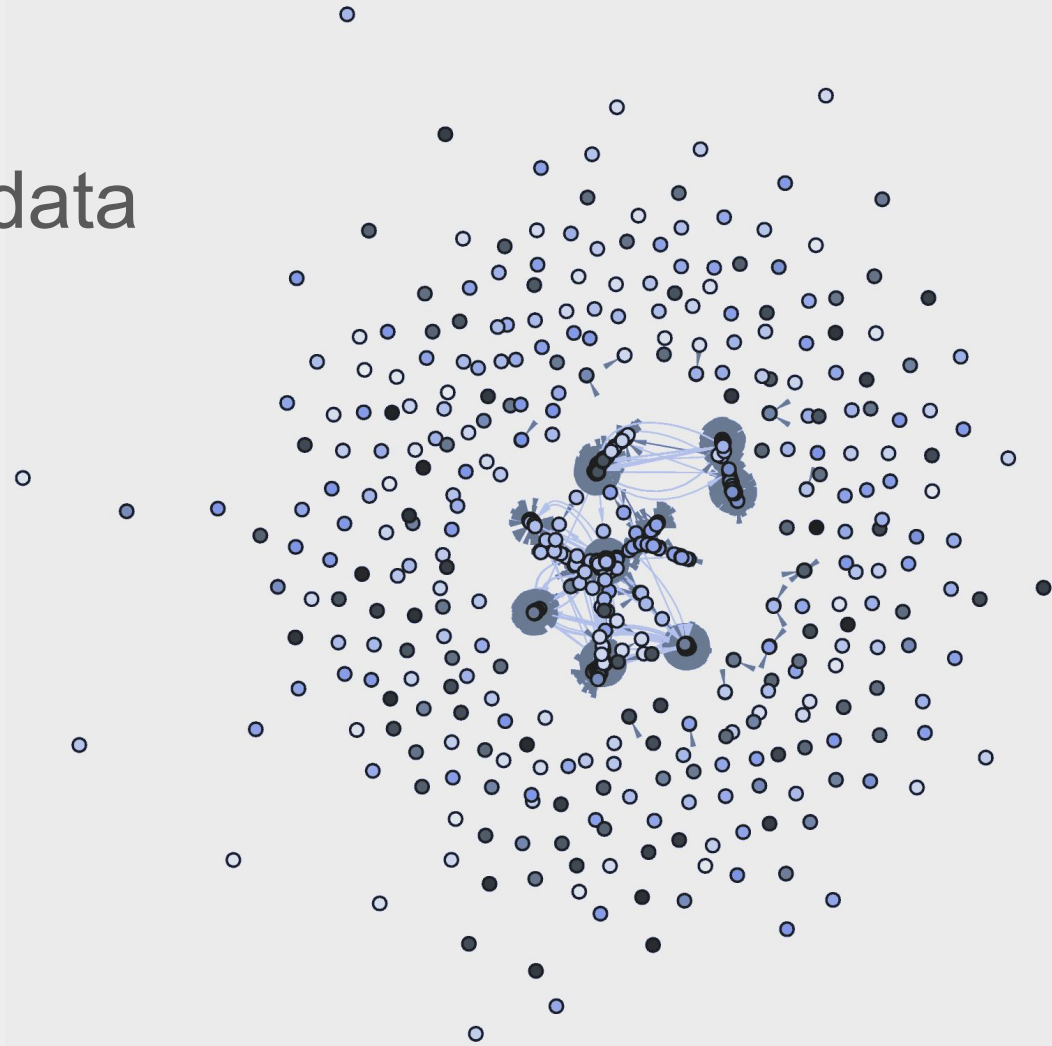


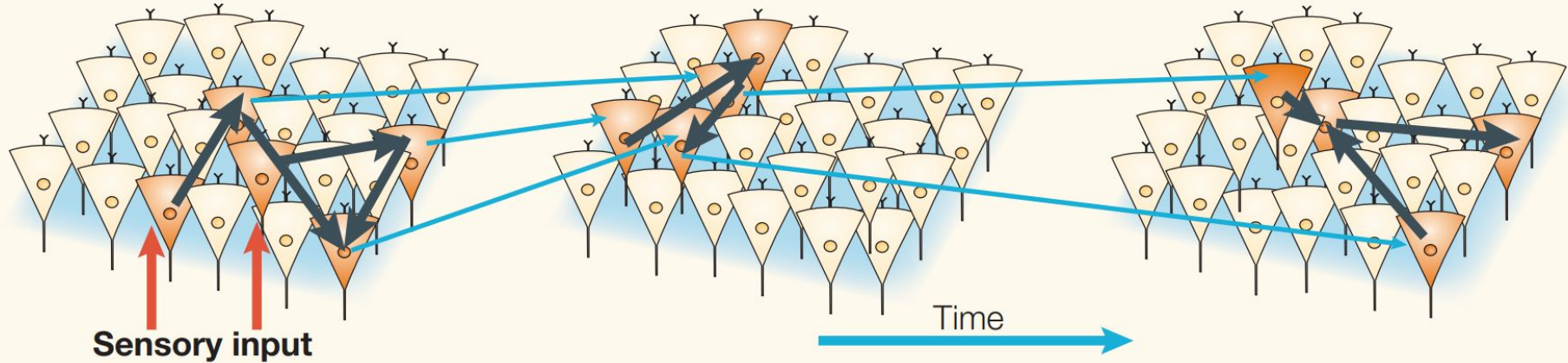
Community detection from large spike-train data

team funci

Juliana, Baruc, Luis, Sara



Question: Groups of coordinated neurons



Question: Groups of coordinated neurons

- Can we detect groups of neurons with coordinated activity?
- How do these groups overlap with brain areas?
- Do these groups change with behavioral states?

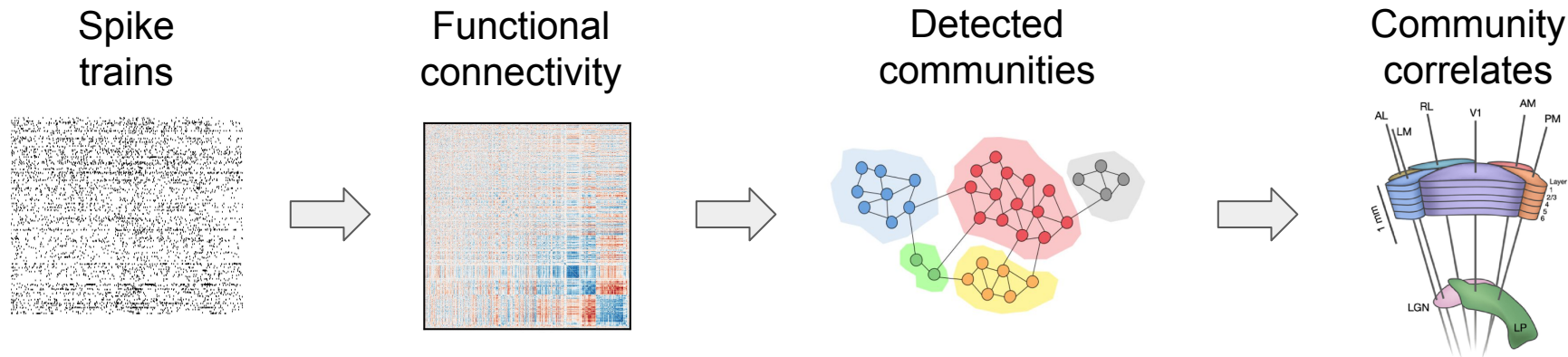
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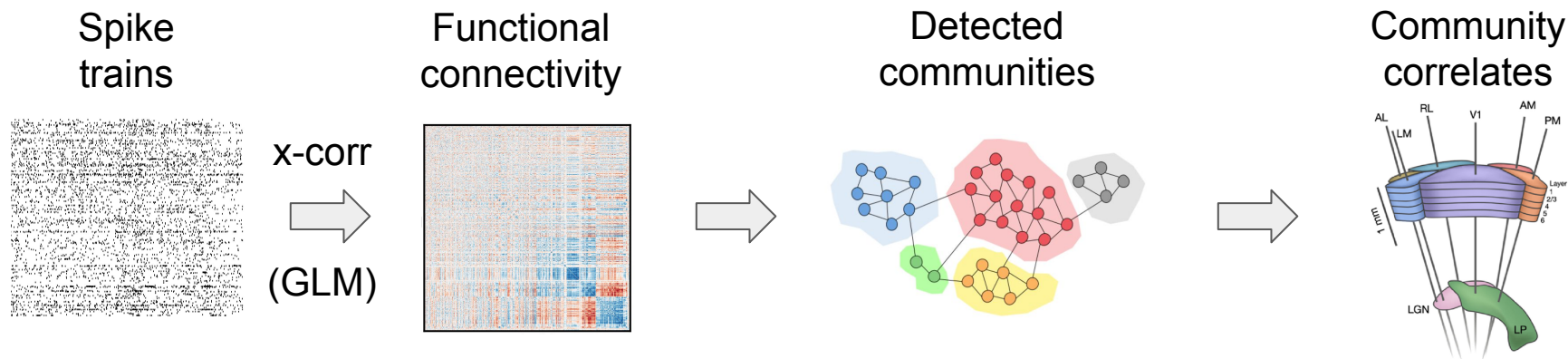
Pipeline



Question: Groups of coordinated neurons

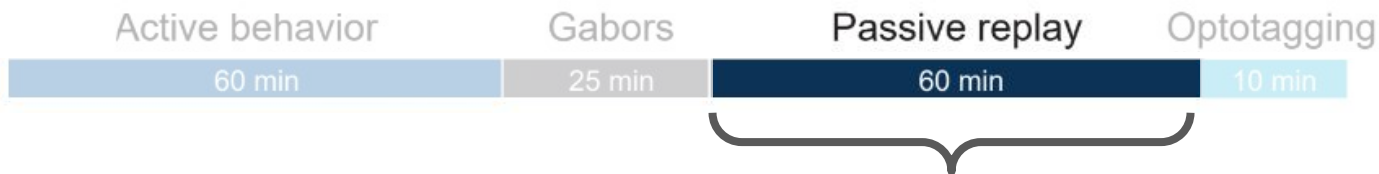
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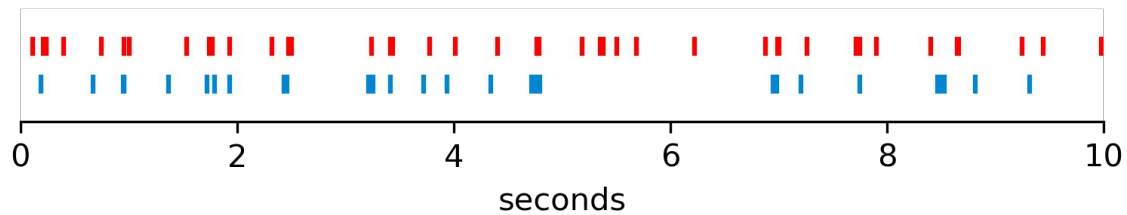
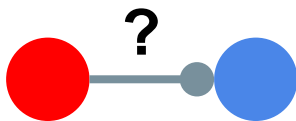


Data

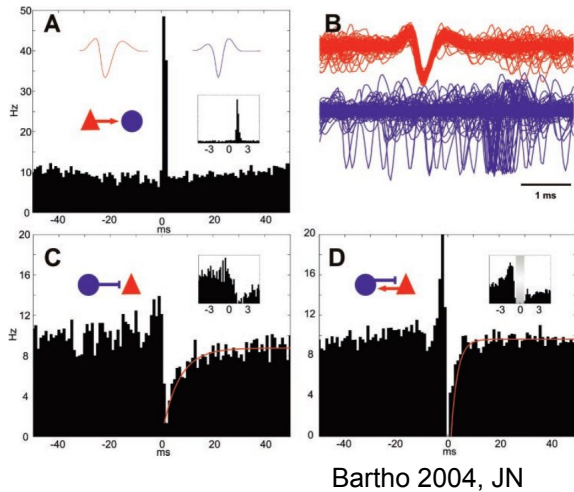
- 1 session, 60 min, passive replay
- Multi-area
- 1,158 good units
- 34,397,026 spikes
- **668,746 pairs**



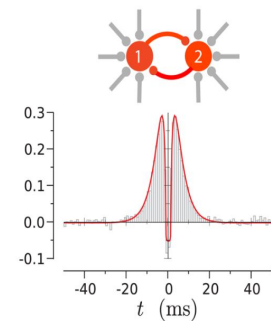
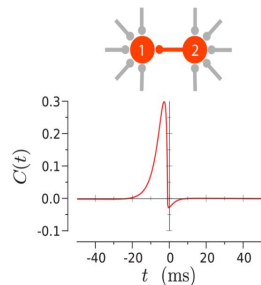
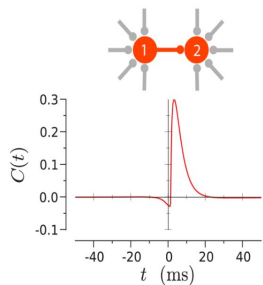
Cross-correlograms



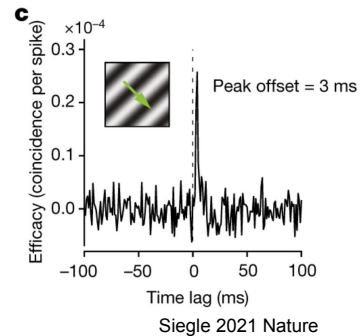
History



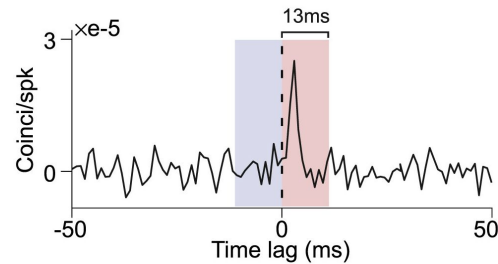
Bartho 2004, JN



Ostojic 2009, JN

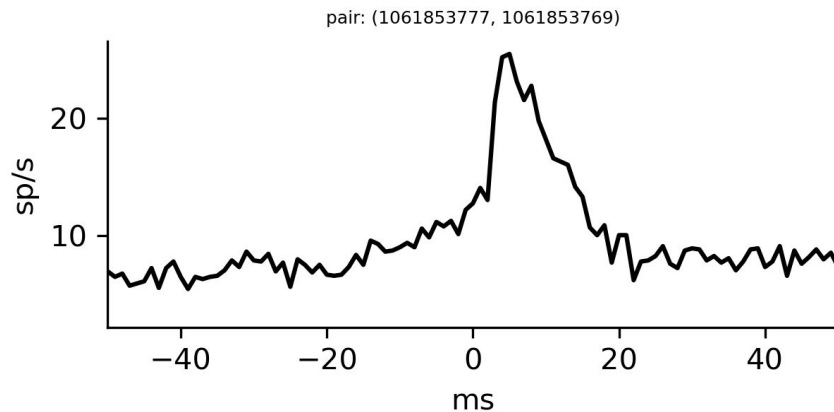
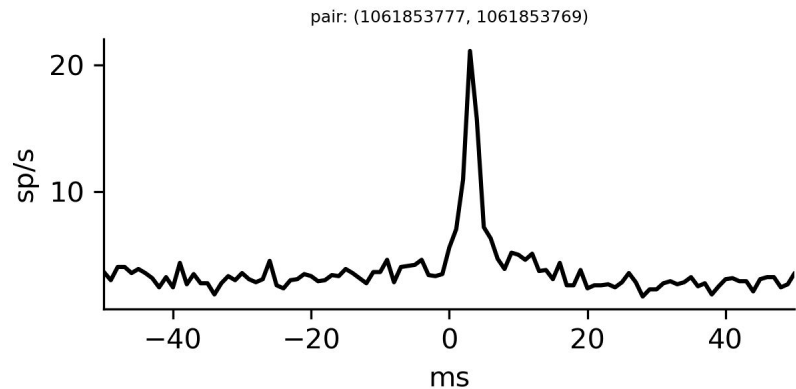


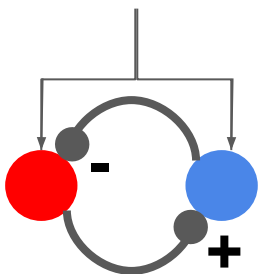
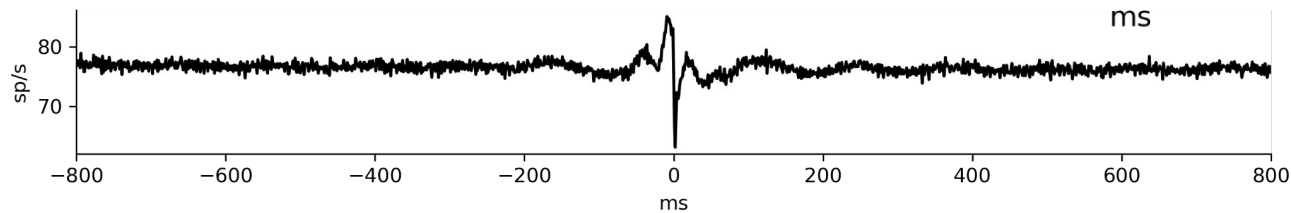
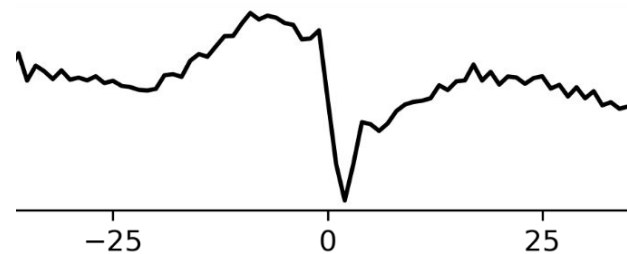
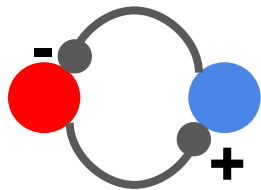
Siegle 2021 Nature



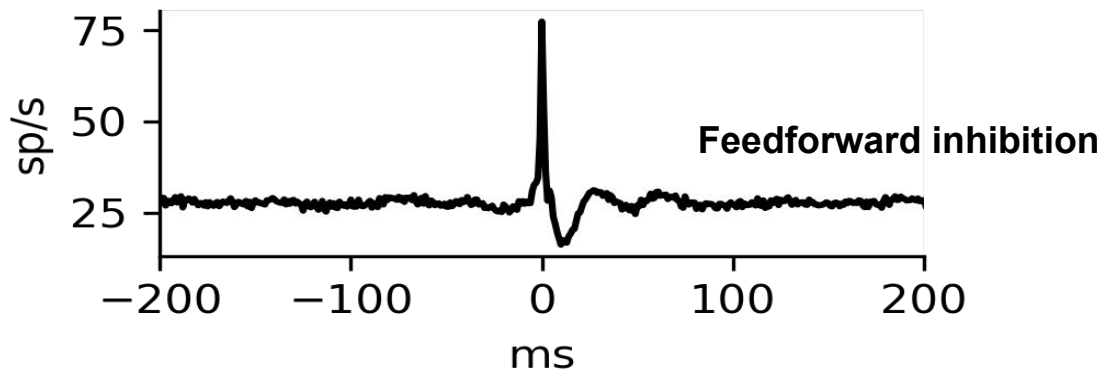
Jia 2022, Neuron

Examples of cross-correlograms from our data

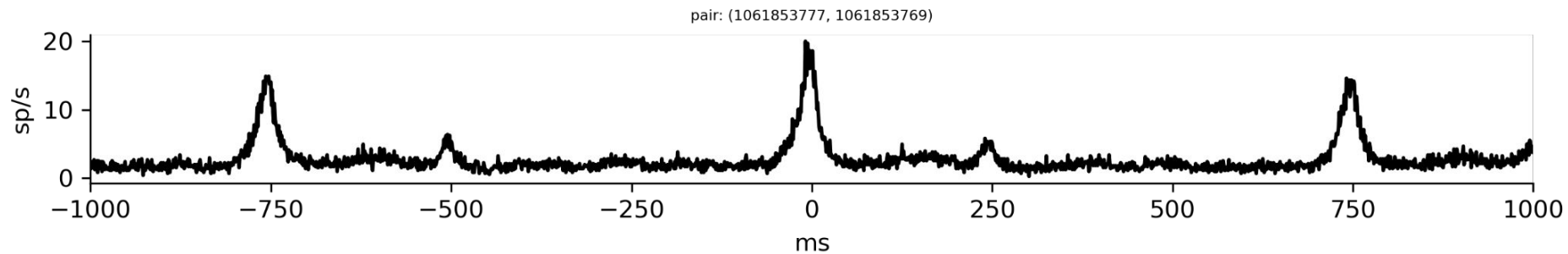




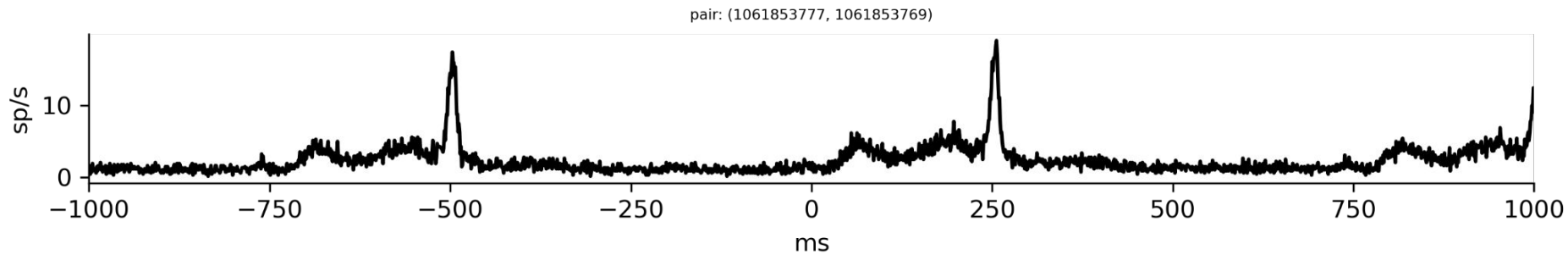
pair: (1061853777, 1061853769)

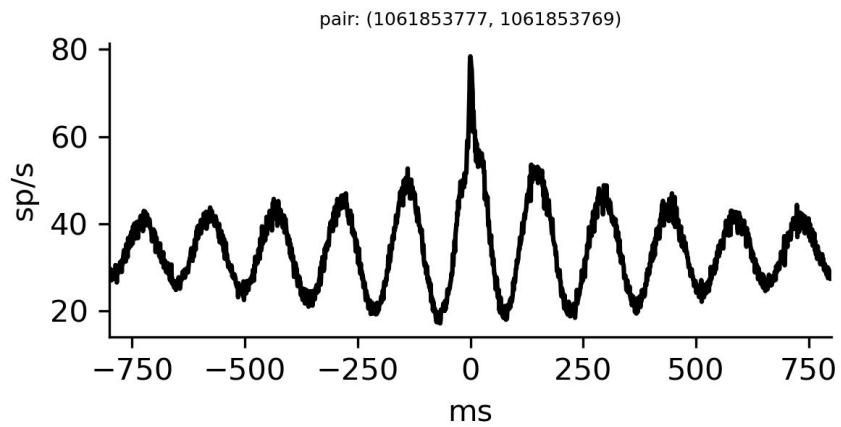
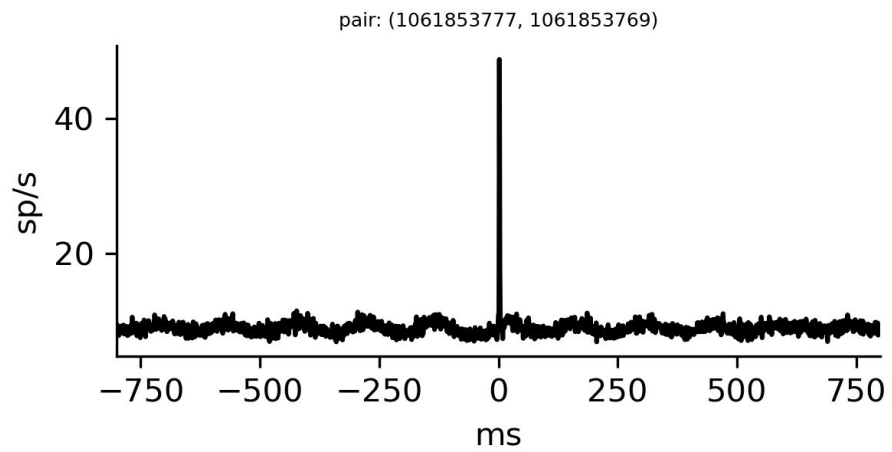


Pair a & b both locked to the stimulus



Pair a & b where a is locked to the start of the stimulus and b is locked to the stop

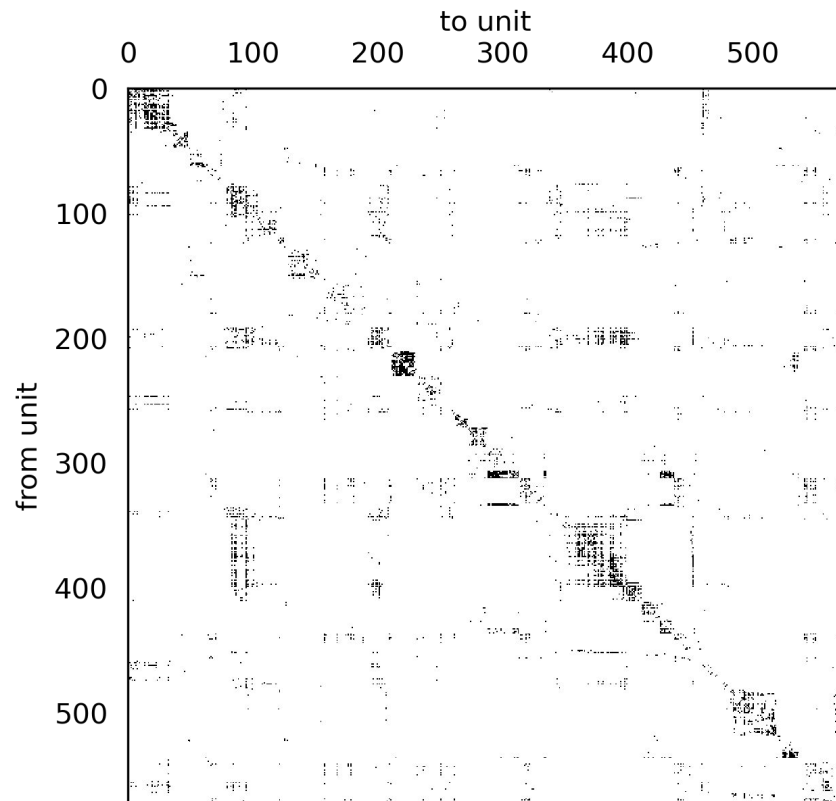




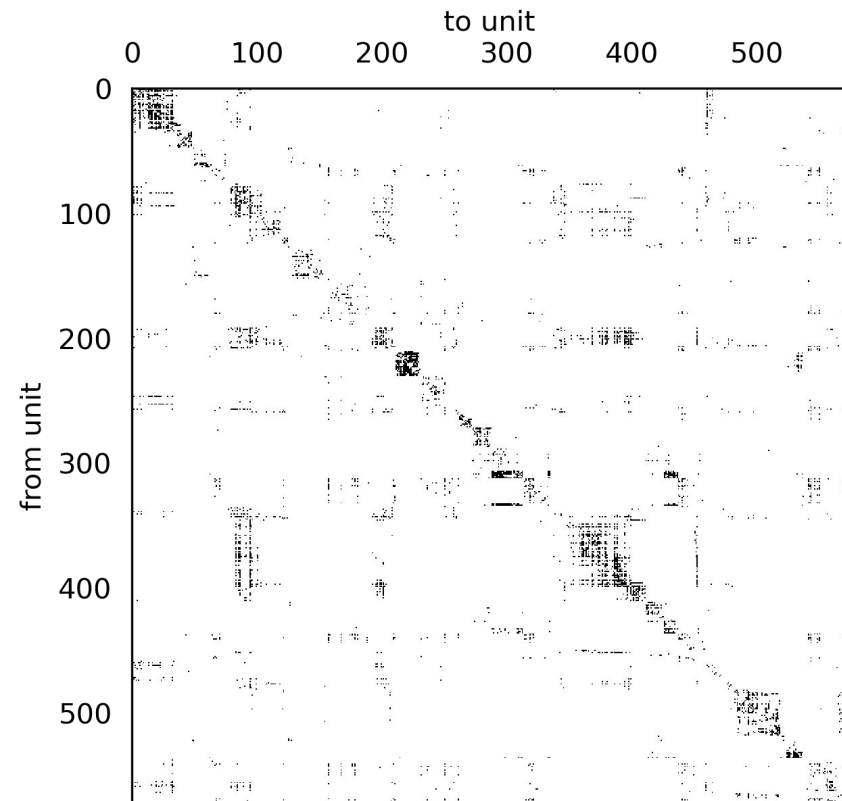
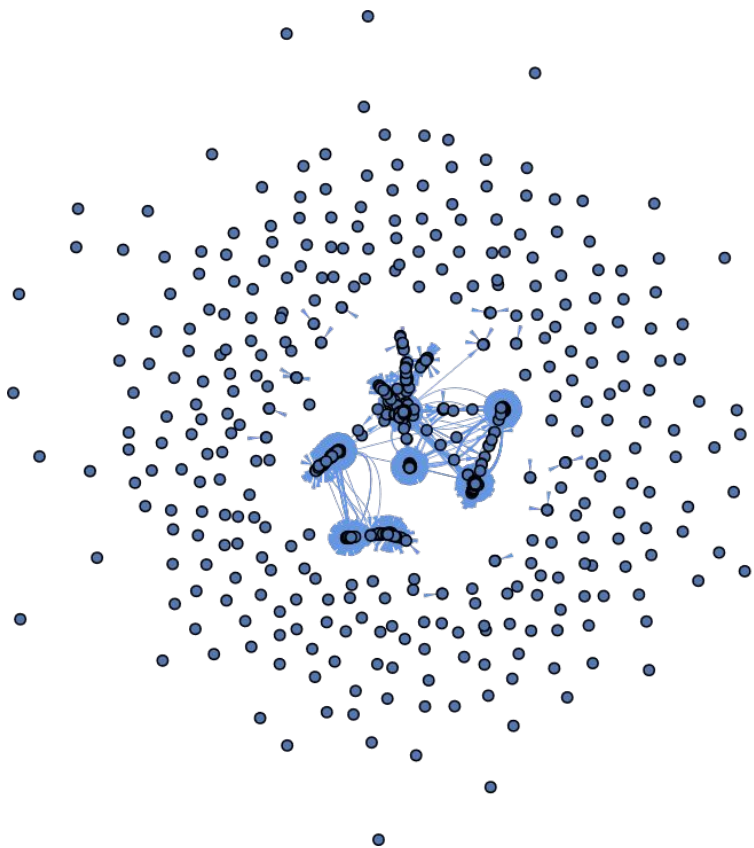
The connectivity matrix

Metric of connectivity

- Cross correlograms with 1ms resolution
- Disregard zero lag peaks
- For now: not looking at inhibition(negative peaks)
- For each pair:
 C_{ij} = z-scored peak in $[0, +200]$ ms
 C_{ji} = z-scored peak in $[-200, 0]$ ms



The connectivity matrix



Community detection

- Groups of densely connected neurons, with sparser connections between groups (groups of highly correlated neurons during passive replay).
- Measure **modularity**

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Q = fraction of edges within communities – expected fraction of such edges

$$Q = \frac{1}{m} \sum_{ij} \left[A_{ij} - \frac{k_i^{\text{in}} k_j^{\text{out}}}{m} \right] \delta_{c_i, c_j}$$

m = total edges in graph

A = adjacency matrix

k_i^{in} = in-degree of node i

k_j^{out} = out-degree of node j

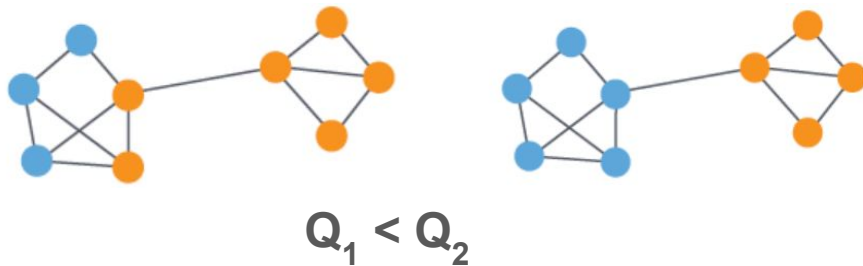
$$\delta_{c_i, c_j} = \begin{cases} 1 & \text{if } c_i = c_j \\ 0 & \text{if } c_i \neq c_j \end{cases}$$

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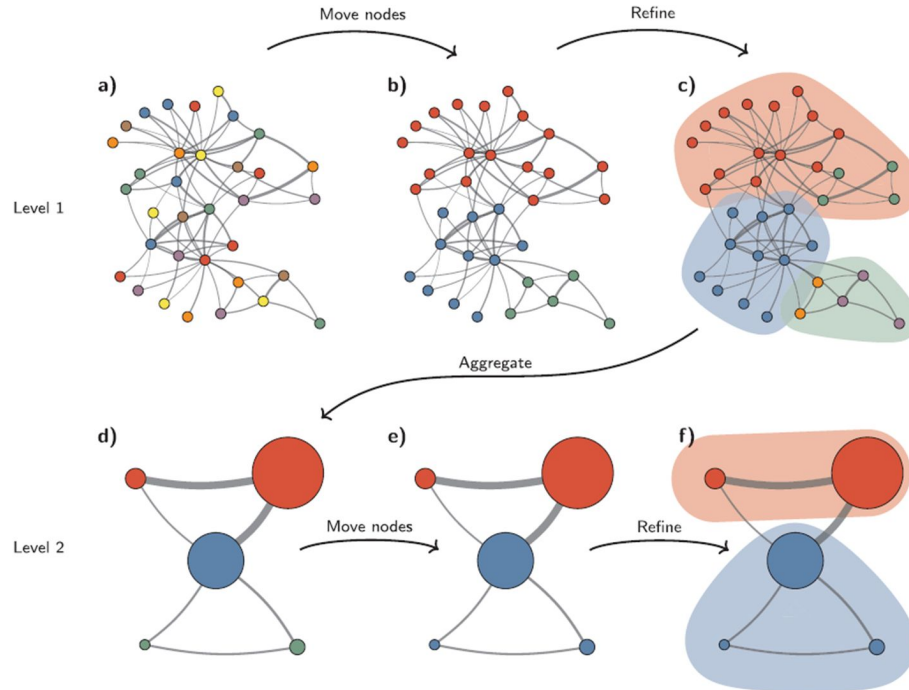
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Leiden algorithm

Greedy modularity optimization algorithm for directed, weighted graphs.



Start with singletons partition

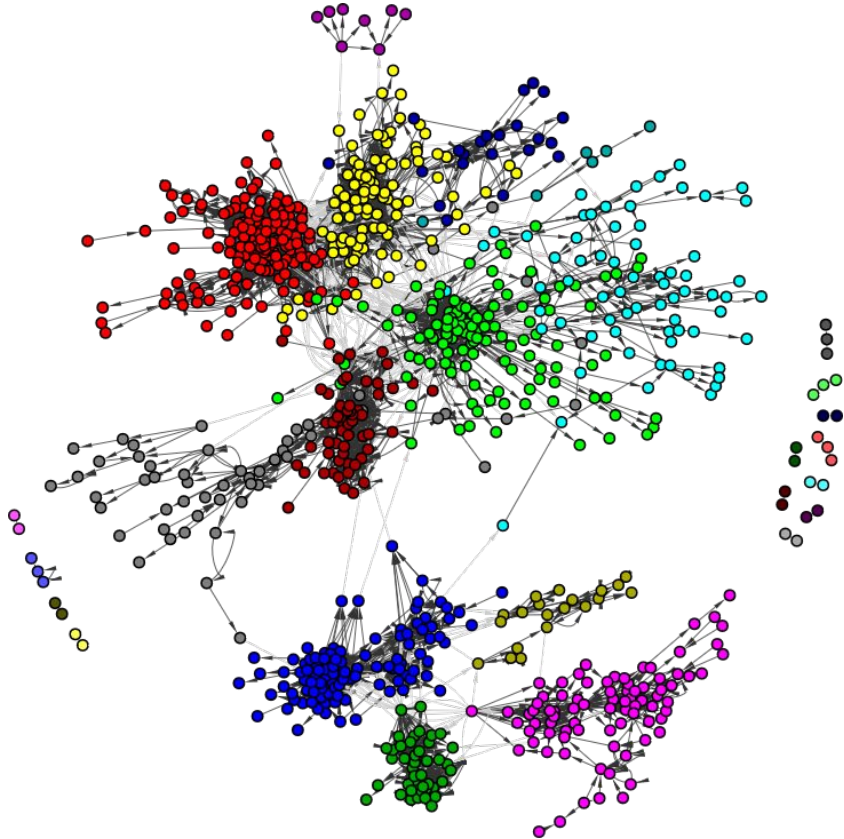
Move nodes: visit all nodes (random order but in a smart way). Determine best community for each (increase in Q).

Refine: avoids having disconnected components

Aggregate: nodes are refined partition and edges are summed across communities

Start over on this new graph.

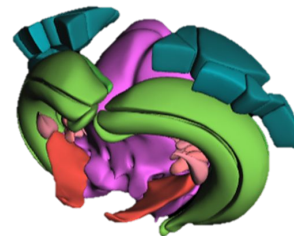
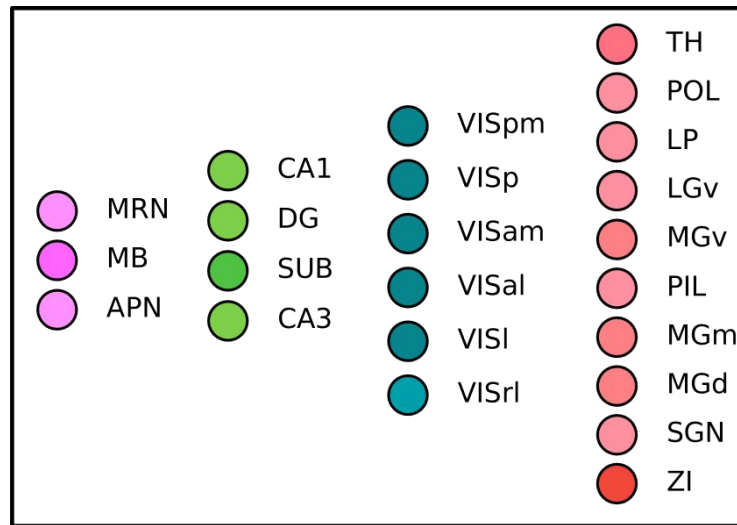
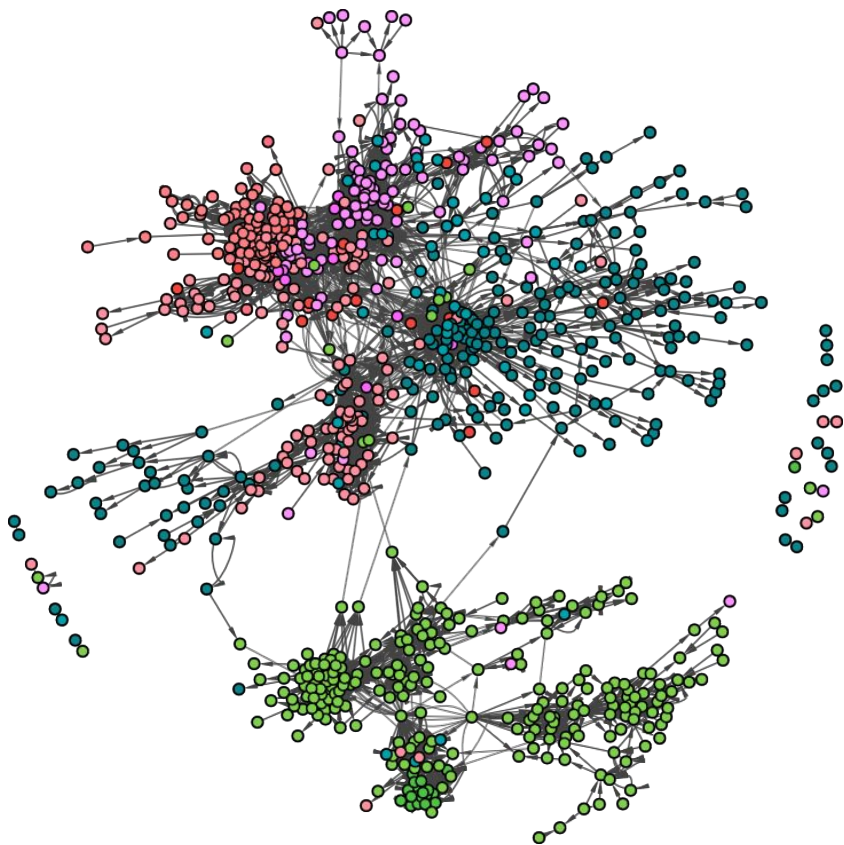
Results: communities



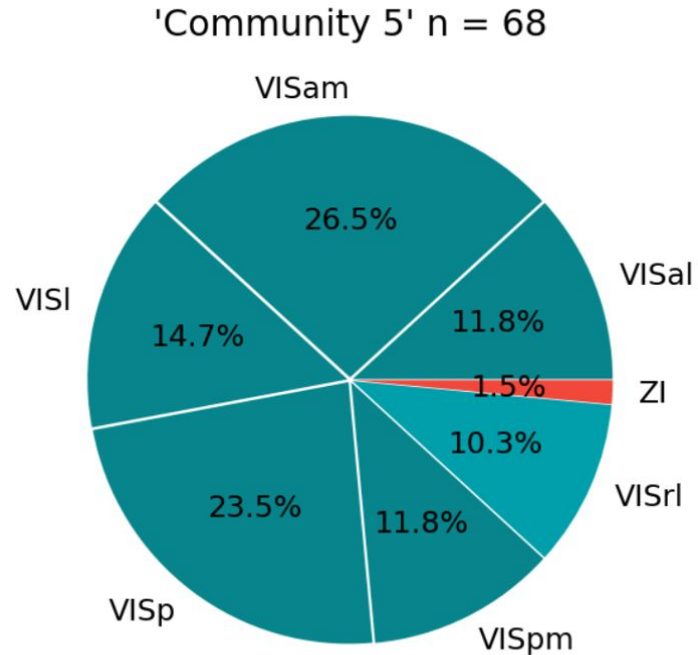
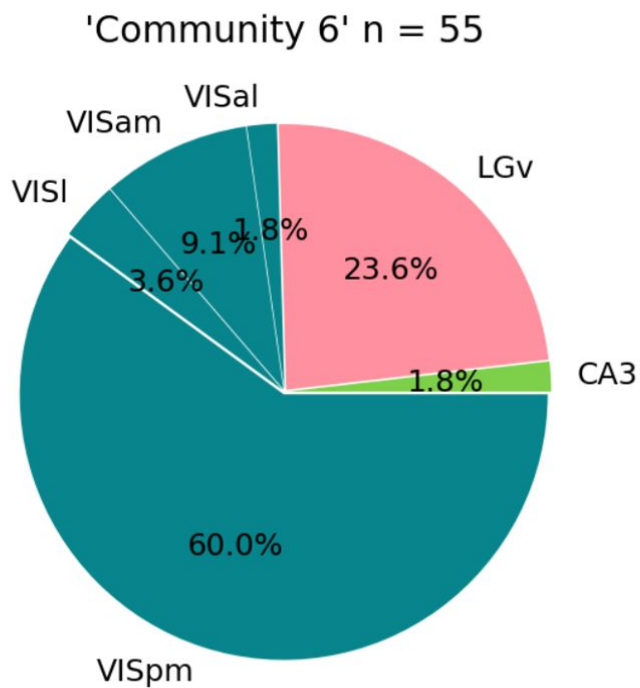
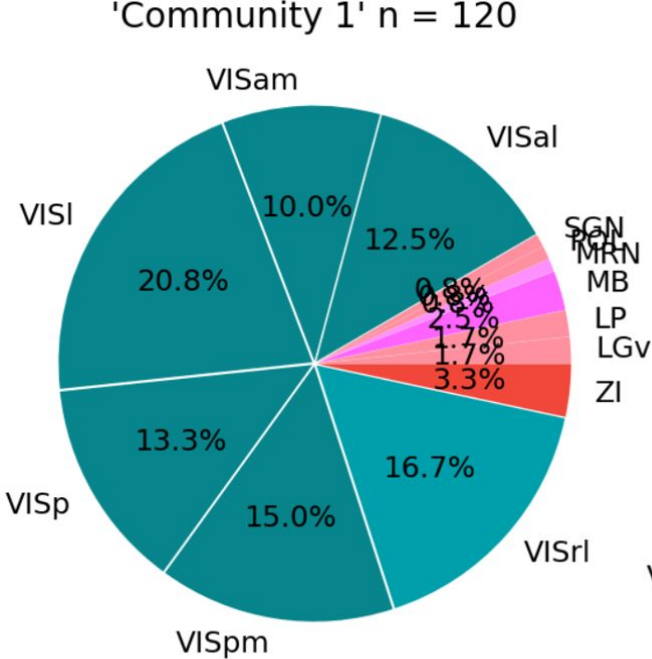
Community ID	Number of members (n)
0	151
1	120
2	103
3	98
4	82
5	68
6	55
7	55
8	45
9	22
10	20
11	8
12	6

Community ID	Number of members (n)
15	3
16	3
13	3
14	3
17	2
18	2
19	2
20	2
21	2
22	2
23	2
24	2
25	2

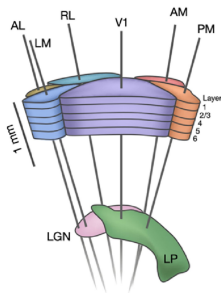
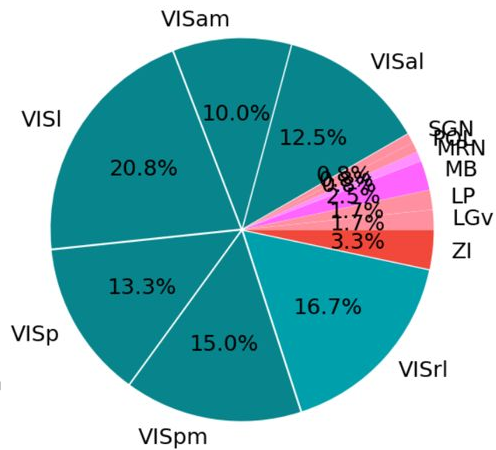
Structure



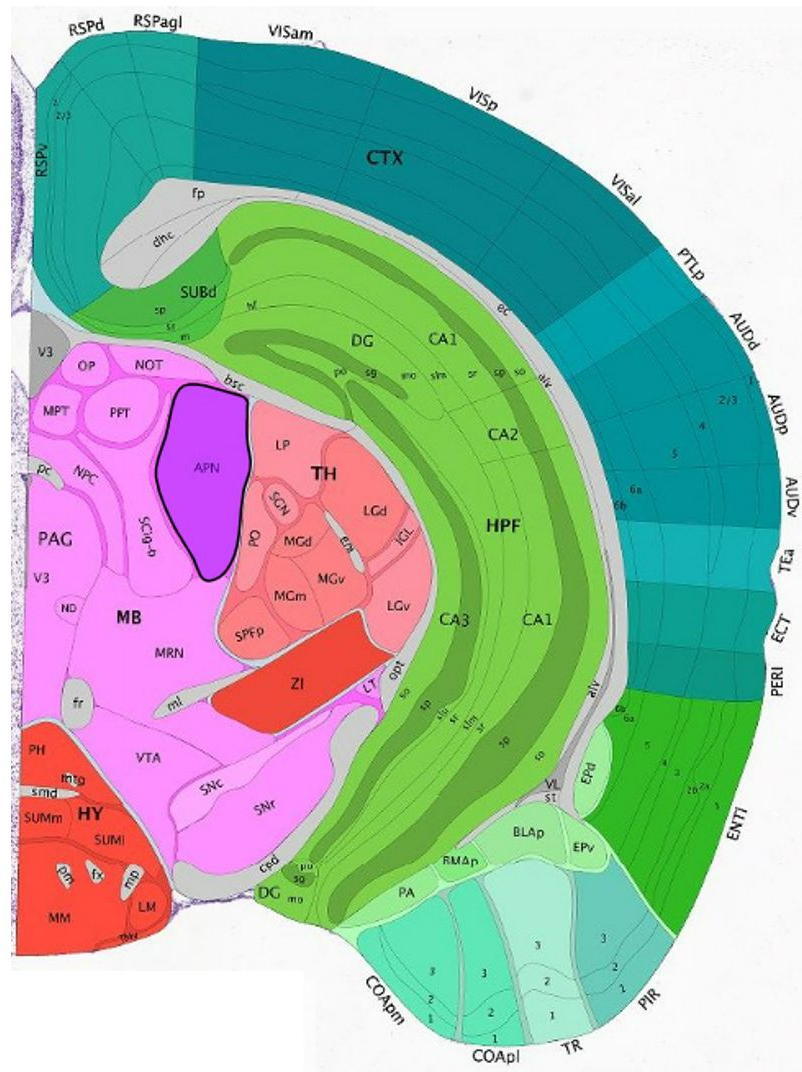
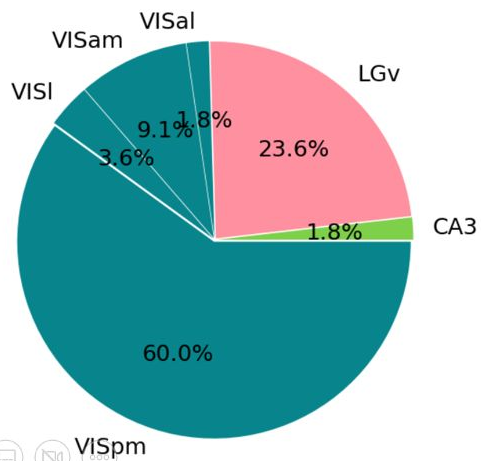
Visual areas



'Community 1' n = 120

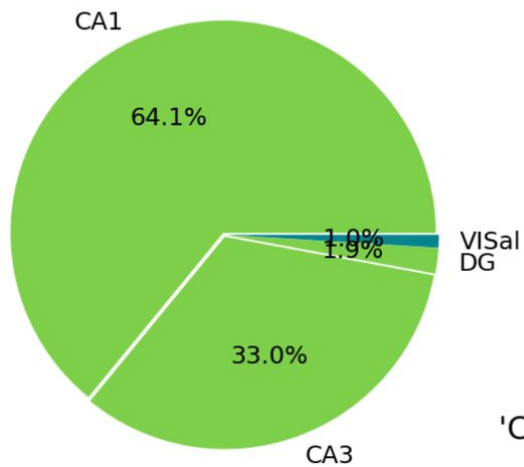


'Community 6' n = 55

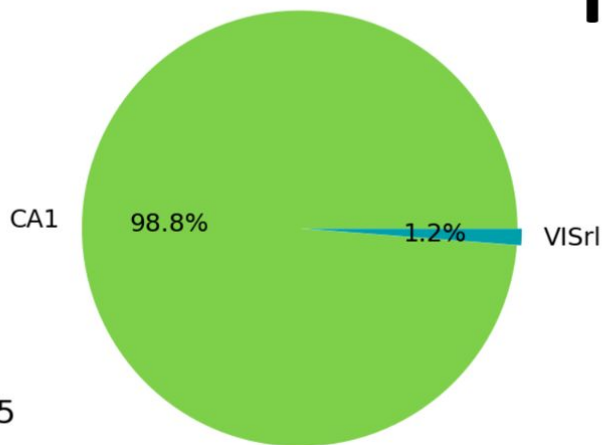


APN
CA1
CA3
DG
LGv
LP
MB
MGd
MGm
MGv
MRN
PIL
POL
SUB
TH
VISal
VISam
VISl
VISp
VISpm
VISr1
ZI

'Community 2' n = 103

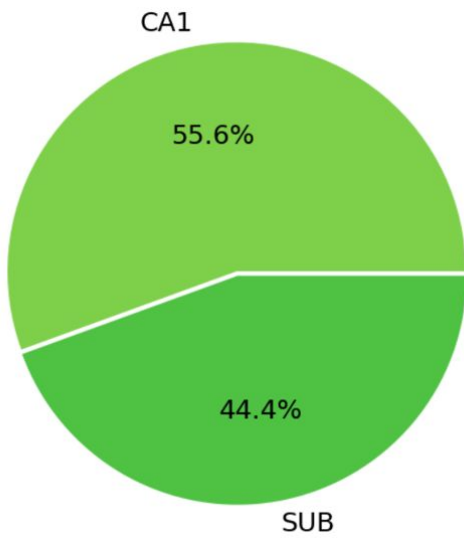


'Community 4' n = 82

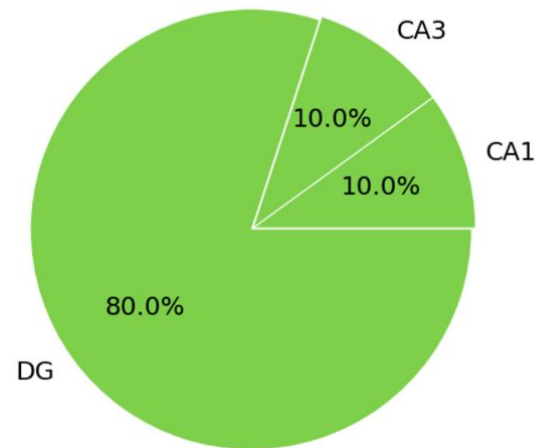


Hippocampal areas

'Community 8' n = 45

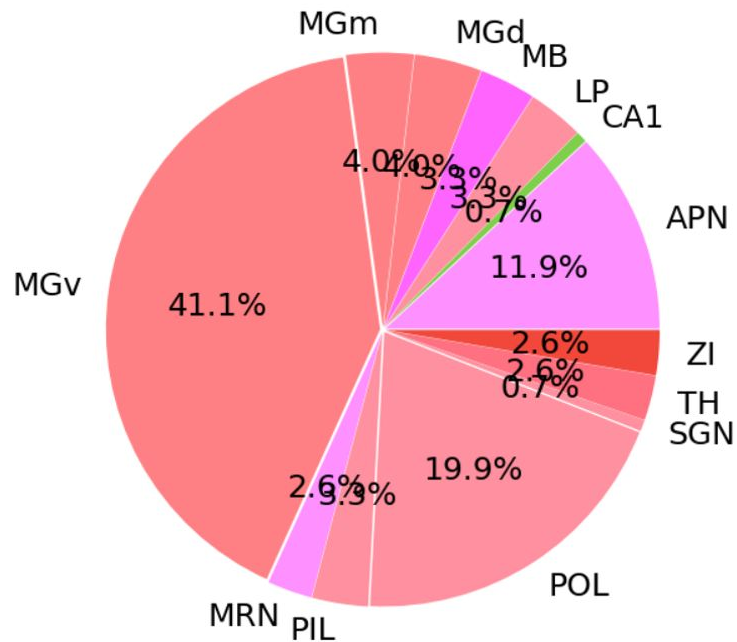


'Community 10' n = 20

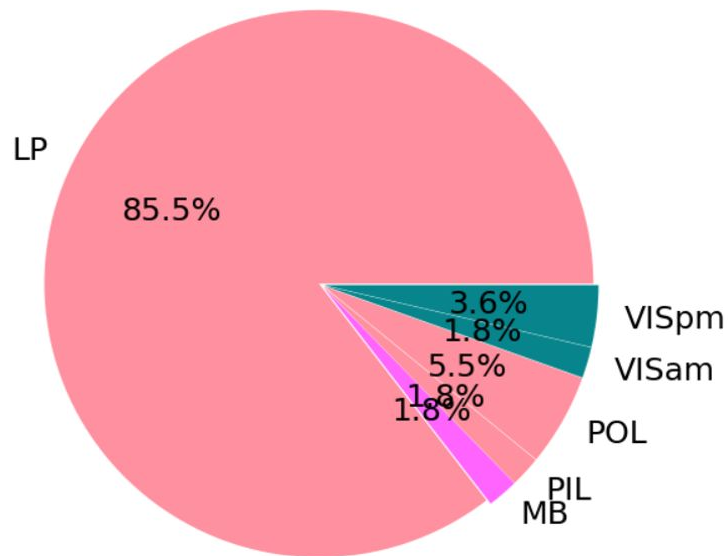


Thalamic areas

'Community 0' n = 151

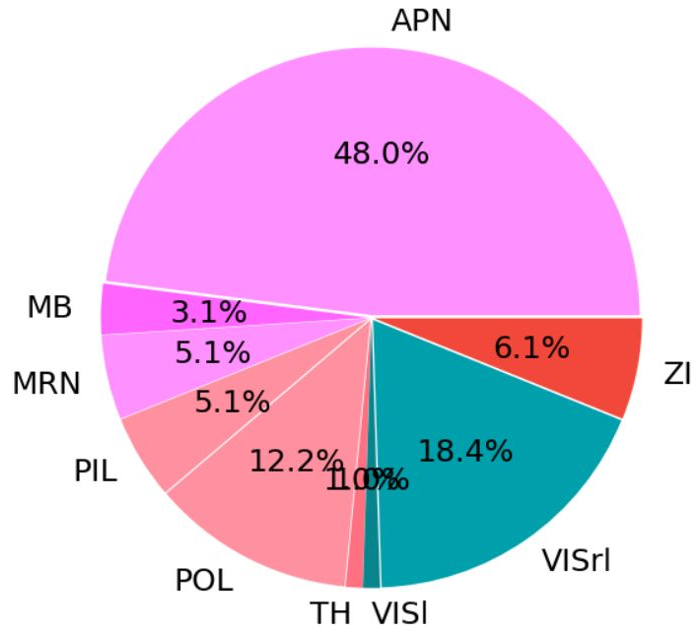


'Community 7' n = 55

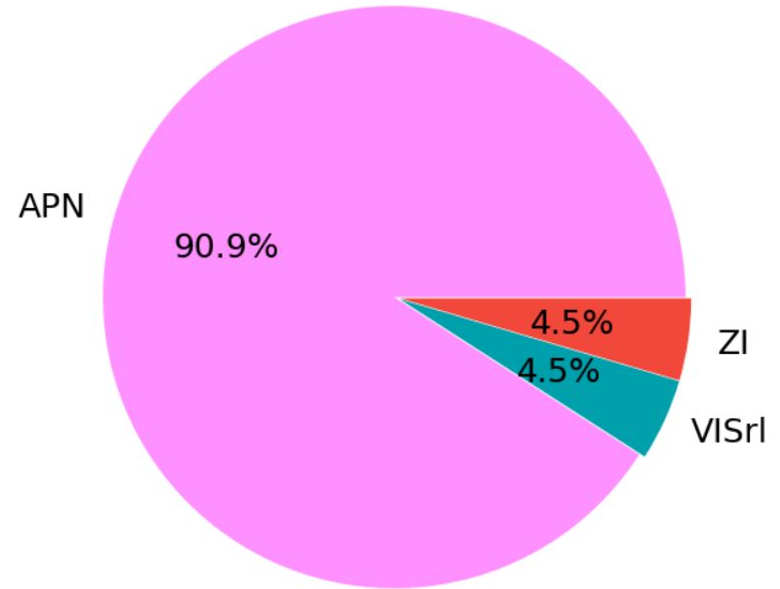


Midbrain areas

'Community 3' n = 98



'Community 9' n = 22



Conclusions

We were able to extract short time-scale pairwise interactions using cross correlograms.

Leiden algorithm proves to be efficient at handling large networks, and succeeds at revealing structure in functional brain networks.

We successfully identified and quantified communities of cells functionally connected in different areas of the brain.

Identifying functional connectivity could shed some light in deciphering the neural circuits involved in a specific behavioral outcome.

Thank you!

Questions?