Opposing engagement of cerebellar and basal ganglia networks with shifts of cortical network topology

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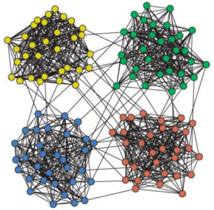
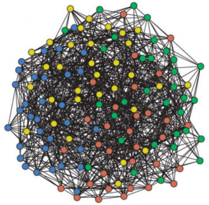
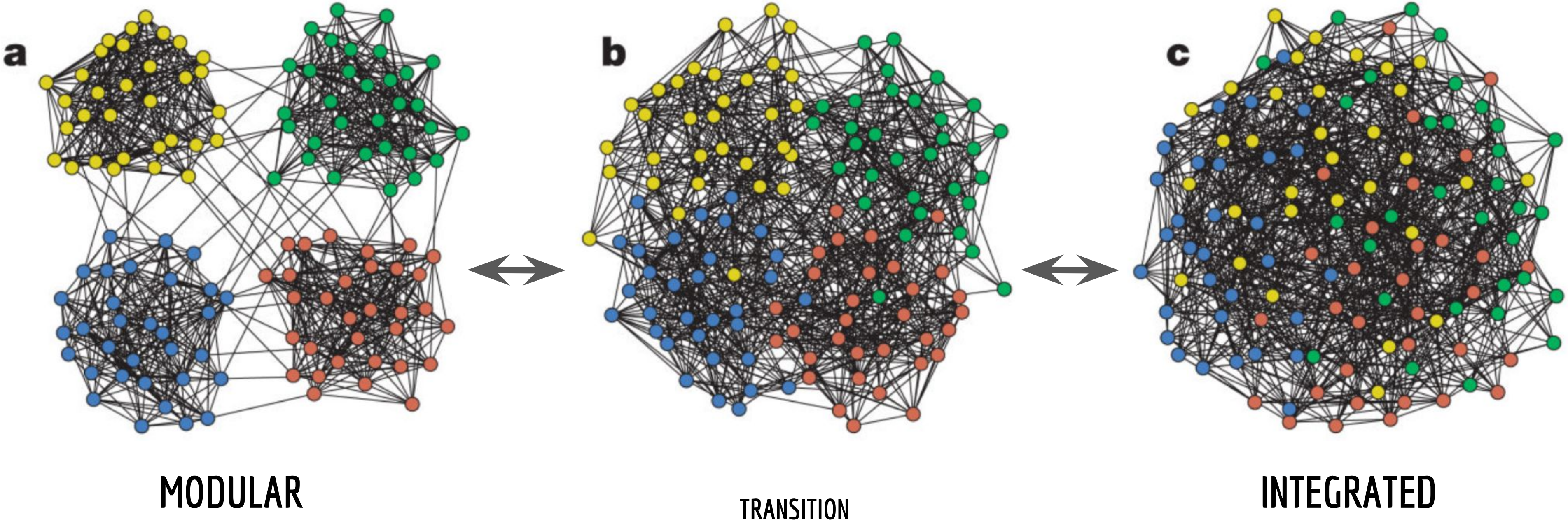
Cognitive flexibility allows you to accomplish a wide range of tasks





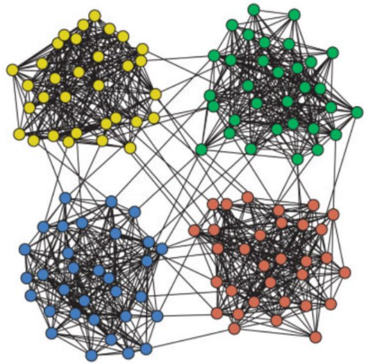
Network connectivity is mutable and can change from modular to integrated



Guimerà & Nunes Amaral, 2005

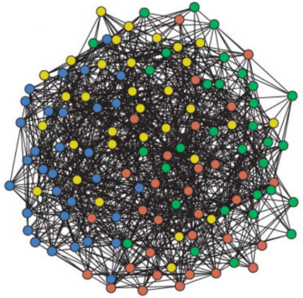
How does the brain adapt to an ever changing landscape?

Reorganization occurs on a fast and slow timescale
(Zhou et al., 2019)

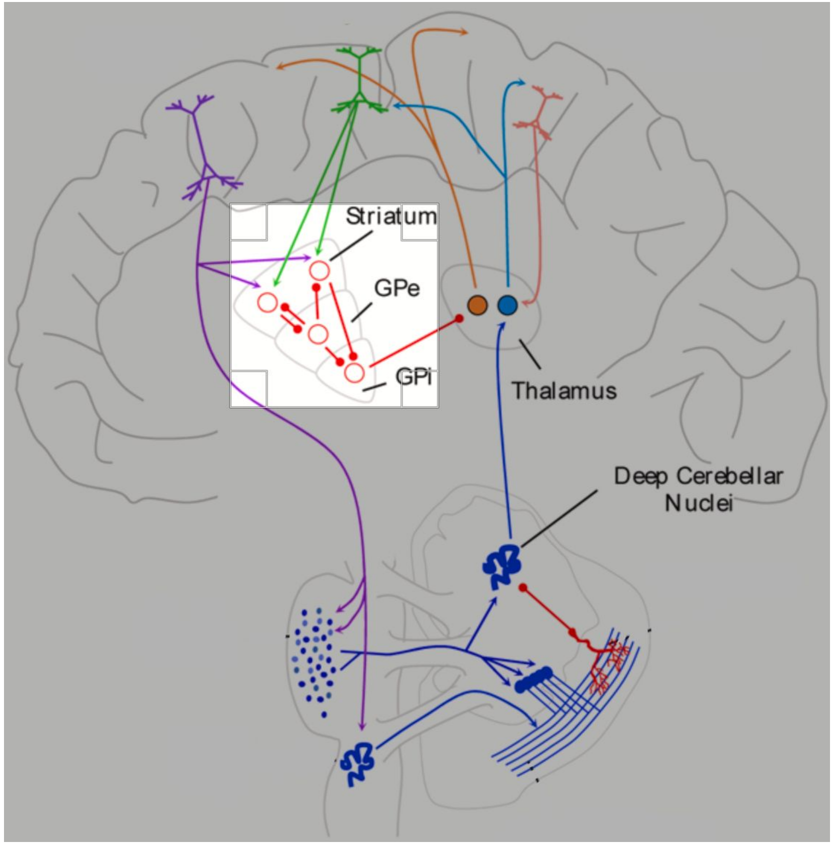


Cortical topology is linked to task cognitive complexity
(Owen et al., 2021)

Cortical topology can indicate richness of memory recall
(Geib et al., 2017)



Subcortical regions are highly connected with cortical regions

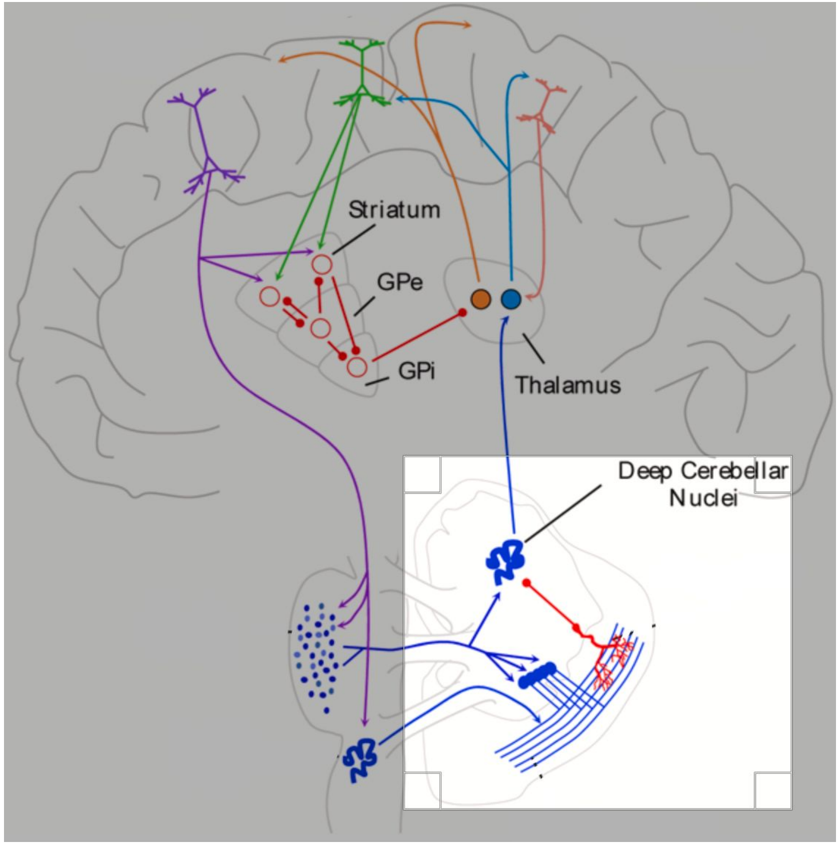


Integration

- Basal ganglia projects to matrix thalamus from globus pallidus interna (GPi).
    - Matrix thalamus projects diffusely to cortical regions

Shine, 2021

Subcortical regions are highly connected with cortical regions

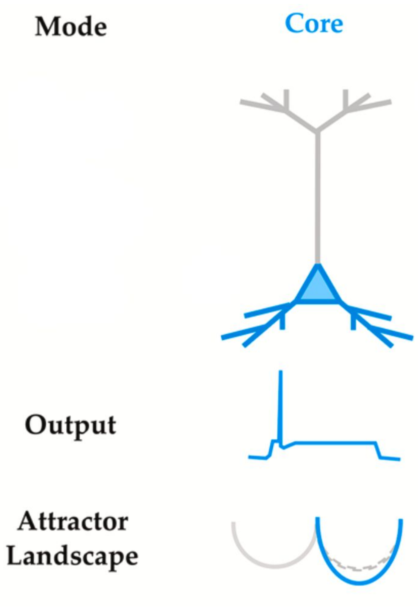


Segregation

- Cerebellum projects to core thalamus from the deep cerebellar nuclei
  - Core thalamus projects focally to cortical hubs

Shine, 2021

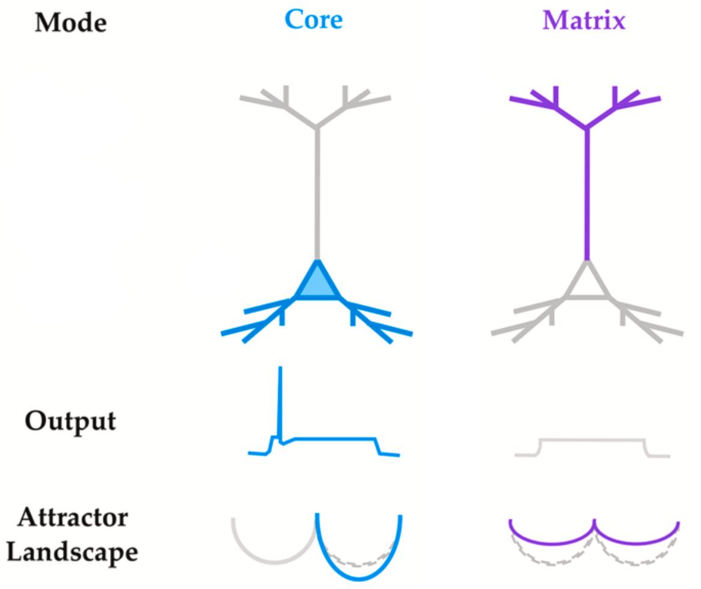
Cellular activation input to the thalamus drive changes in the attractor landscape



- Segregation leads to deepening of the wells
    - Greater stores of energy to select regions
    - Excitatory, glutamatergic input from the deep cerebellar nuclei to core thalamus (Shine, 2021).

Shine, 2021

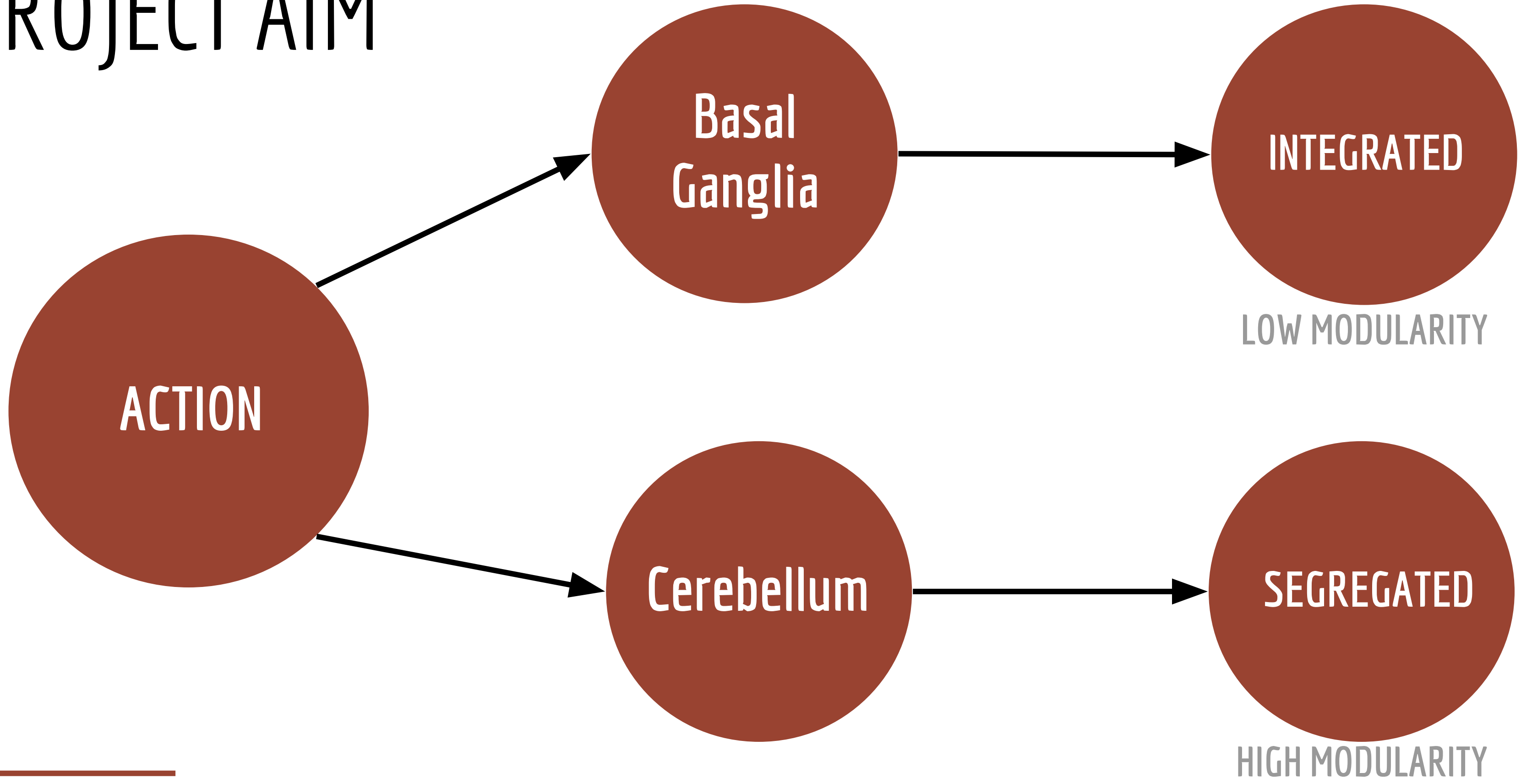
Cellular activation input to the thalamus drive changes in the attractor landscape



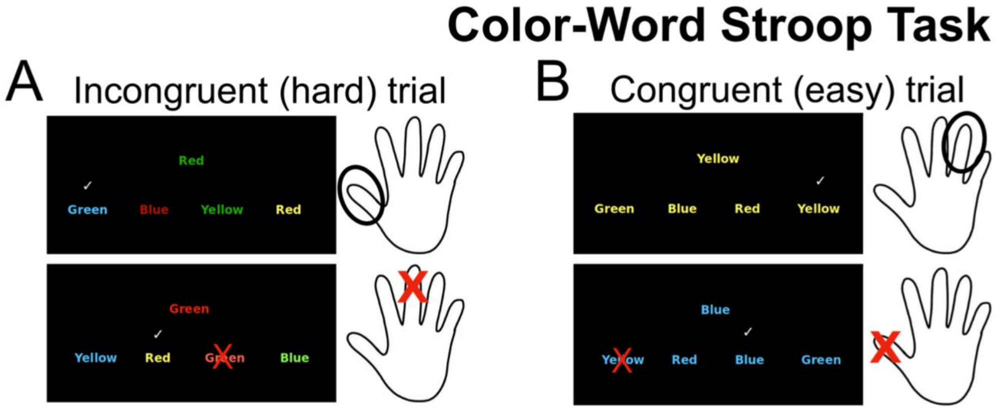
- Segregation leads to deepening of the wells
  - Greater stores of energy to select regions
  - Excitatory, glutamatergic input from the deep cerebellar nuclei to core thalamus (Shine, 2021).
- Shallowing of wells and global integration
  - Less energy stored in regions, but spread across landscape
  - Inhibitory GABAergic cells of the GPi to matrix thalamus cause tonic inhibition causing cortical activation (Shine, 2021).

Shine, 2021

PROJECT AIM


Basal Ganglia
INTEGRATED
LOW MODULARITY
ACTION
Cerebellum
SEGREGATED
HIGH MODULARITY

METHODS



Participants - total n=242

Female=119, Male=123

Mean age=40 ± 6 years, min=30, max=51

Scanner - Siemens 3T Trio

12-channel head coil

fMRI = T2*weighted; 3mm isotropic; RT = 2s; ET = 28ms; Flip = 90°

Task Acquisition - Stroop Task and Multi-Source Interference Task (MSIT)

Adaptive dependent on participant accuracy only in incongruent blocks

Interleaved, four congruent and four incongruent blocks (60s), rest (10s)

Rasero et al., 2021

METHODS

Data analysis

Shen functional atlas parcellation - determinines clusters of brain areas, where k=268

Edge time series - fMRI analysis method, allows examination of network across entire timescale

Modularity index

Estimate value Q, for modularity across a network

Automatically determines segmented communities

Eigenvector centrality

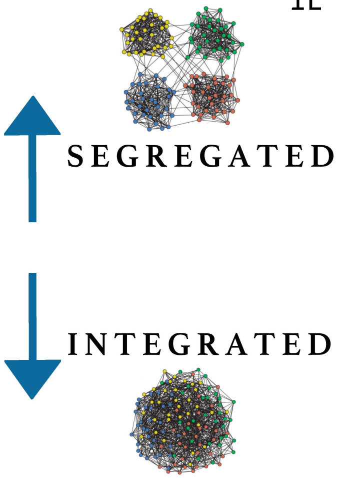
Recursively determines centrality for children of target node

Cross correlation

Determines time lagged relationships between Bg, Cb and cortex

Shen, 2021
Zamani Esfahlani et al., 2021
Shine et al., 2016
Newman, 2010

METHODS: Detailed

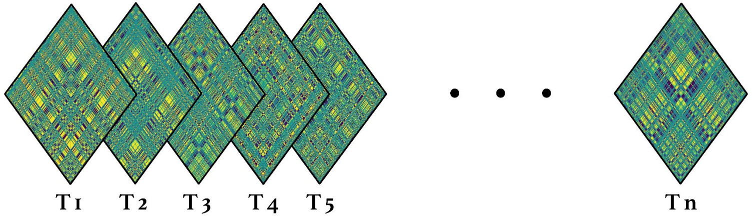


Edge time series

$$z_i = \frac{x_i - \mu_i}{\sigma_i}$$

$$Let\ c_{ij} = [z_i(1) \cdot z_j(1), \ldots, z_i(T) \cdot z_j(T)]$$

$$and\ c_{uv} = [z_u(1) \cdot z_v(1), \ldots, z_u(T) \cdot z_v(T)]$$



Modularity index

$$B = A - P$$

Modularity matrix

Observed

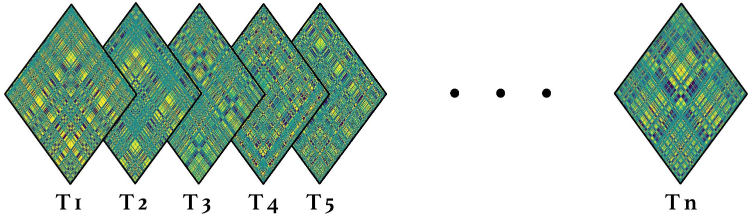
Expected

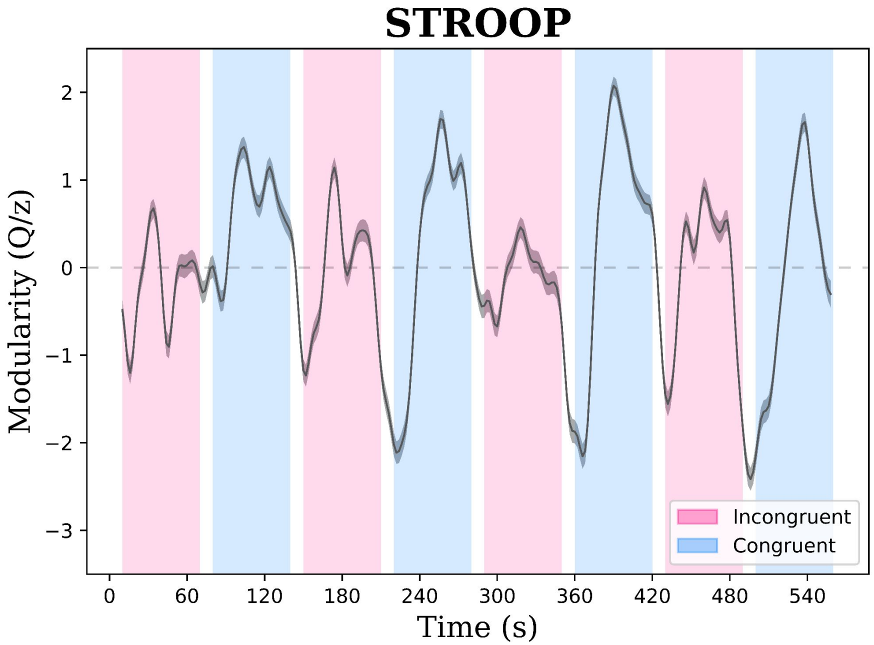
$$Q^{signed} = \sum_{ij} [B_{ij}^{+} - B_{ij}^{-}]\delta\left(\sigma_i, \sigma_j\right)$$

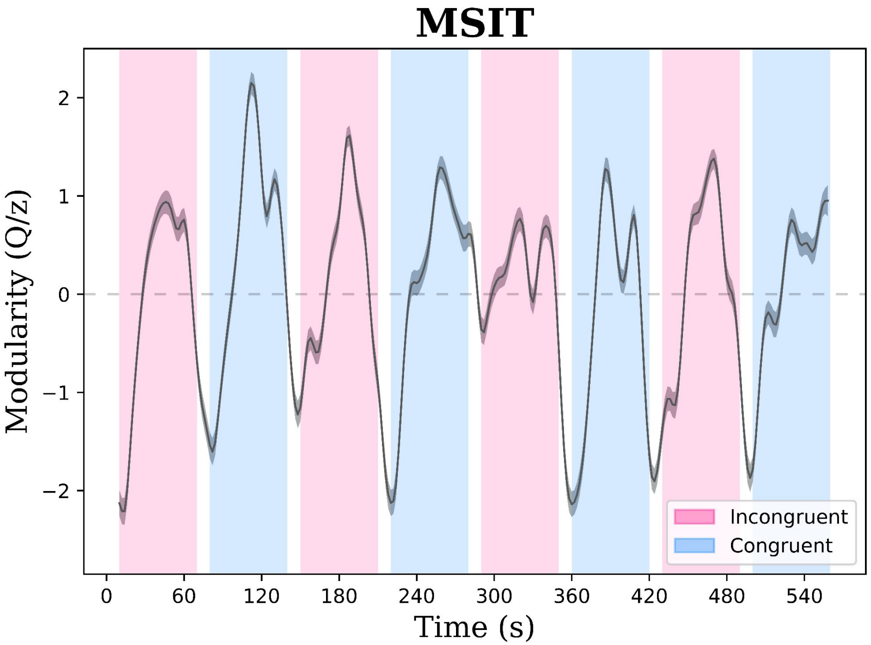
Kronecker function

RESULTS: AIM 1

Modularity Index

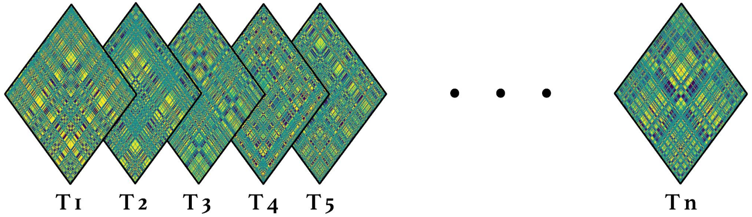


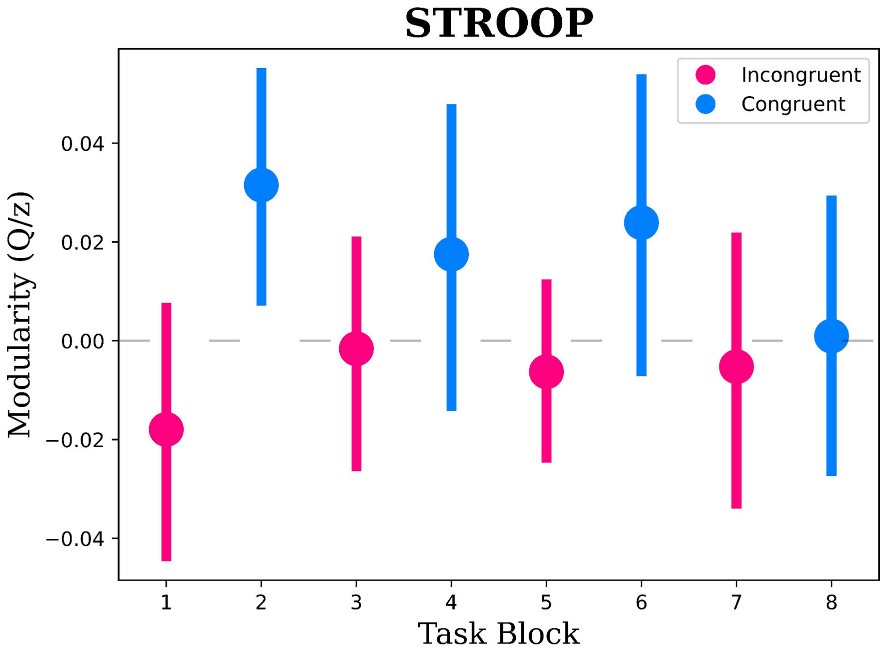


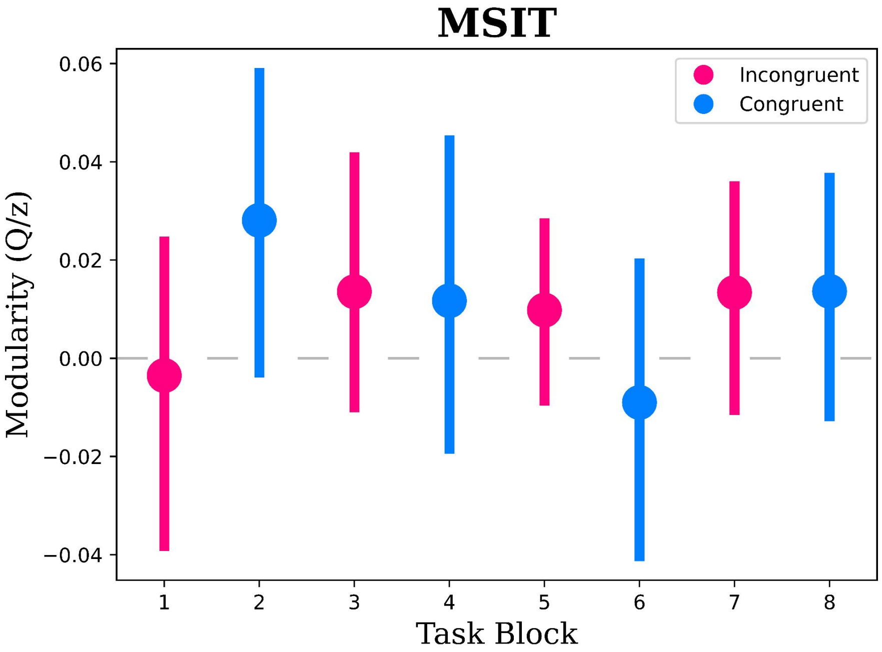


RESULTS: AIM 1

Modularity Index







METHODS: Detailed

MORE ENGAGEMENT

LESS ENGAGEMENT

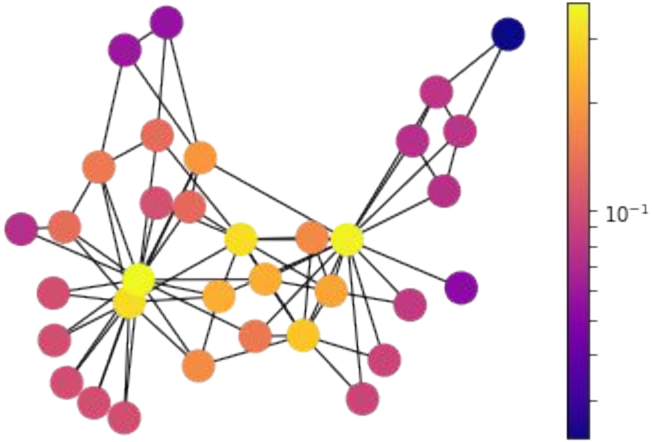
Eigenvector centrality

$$x_i = K_1^{-1} \sum_j A_{ij} x_j$$

Maximum eigenvalue

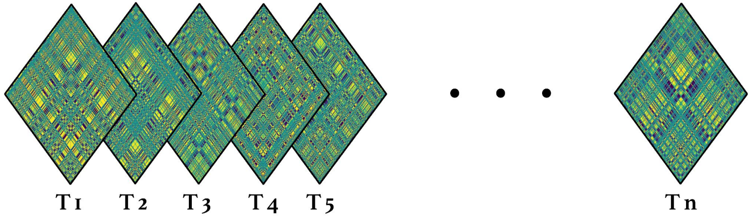
Adjacency matrix

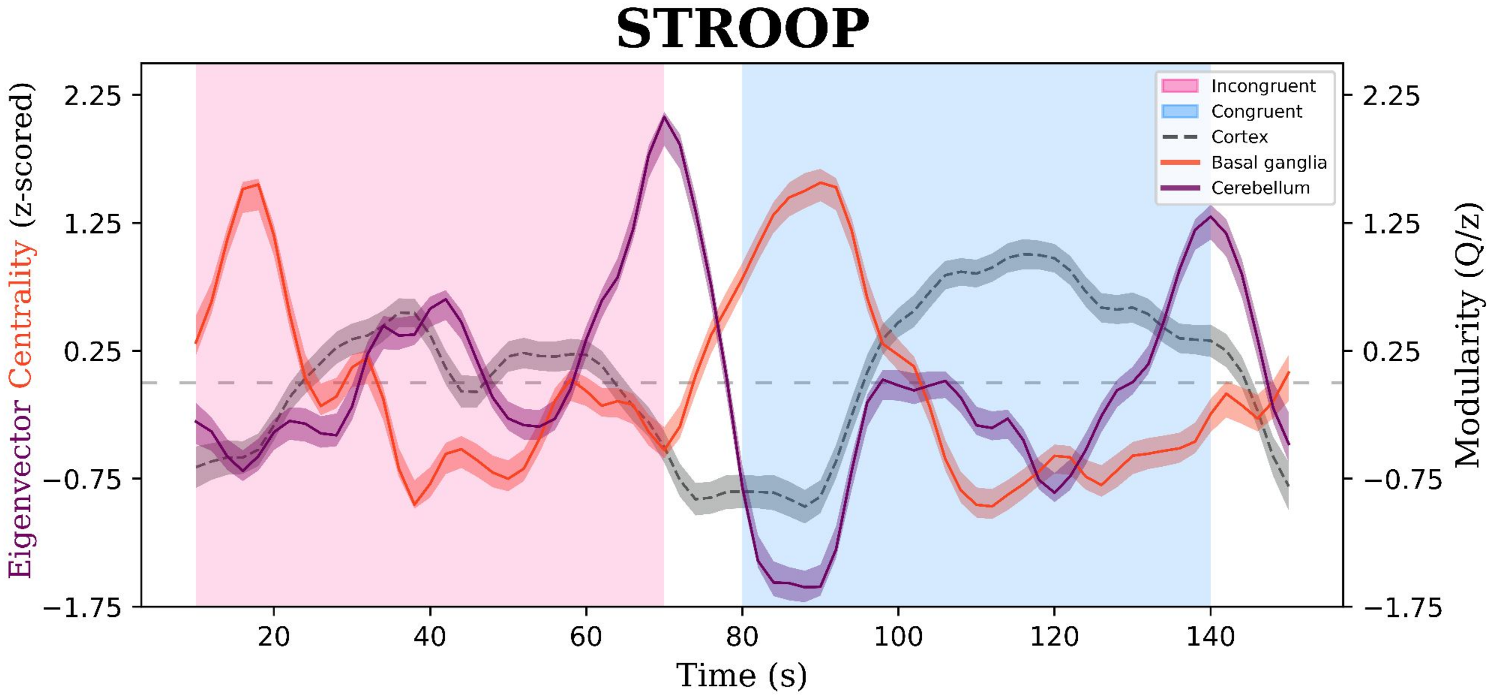
Child node eigenvector



RESULTS: AIM 2

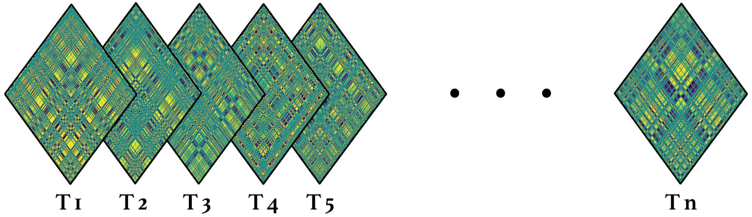
Eigenvector Centrality

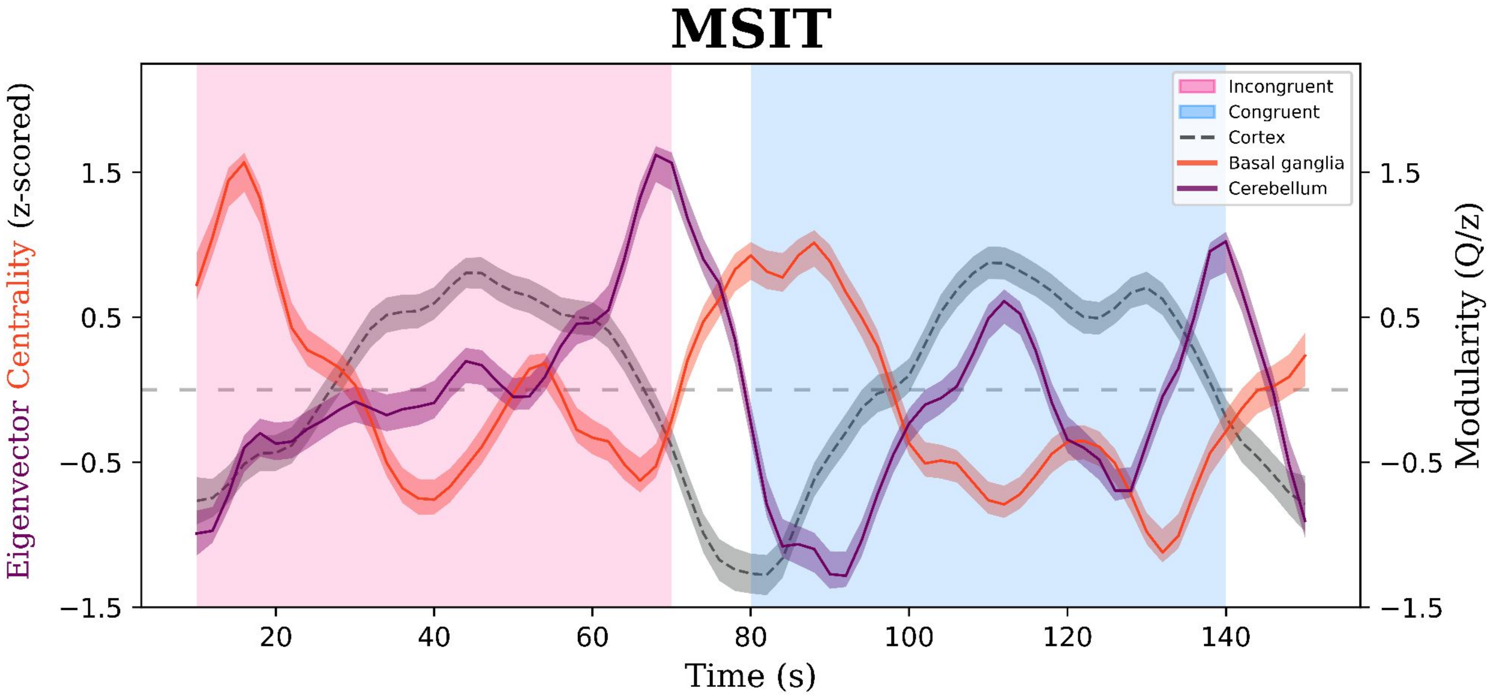




RESULTS: AIM 2

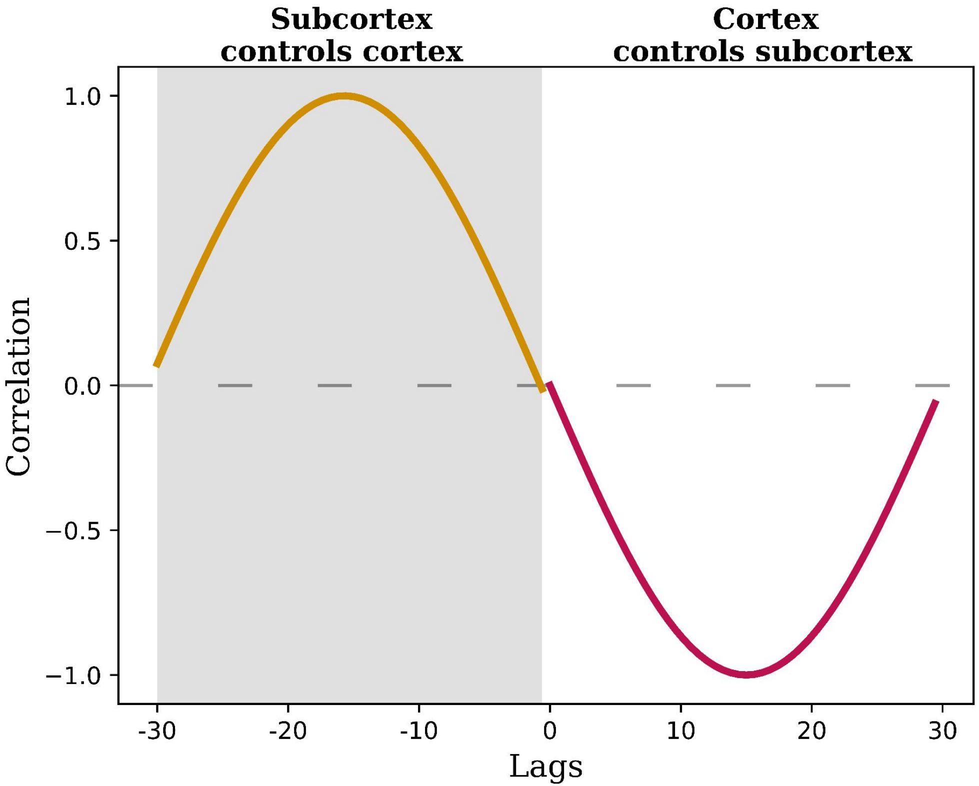
Eigenvector Centrality





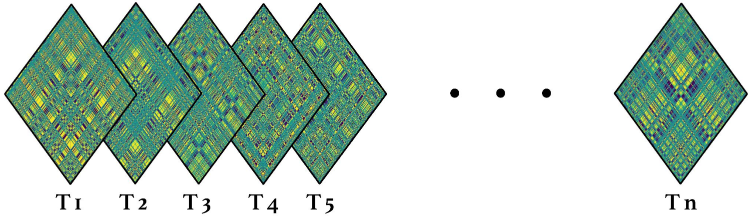
CROSS CORRELATION

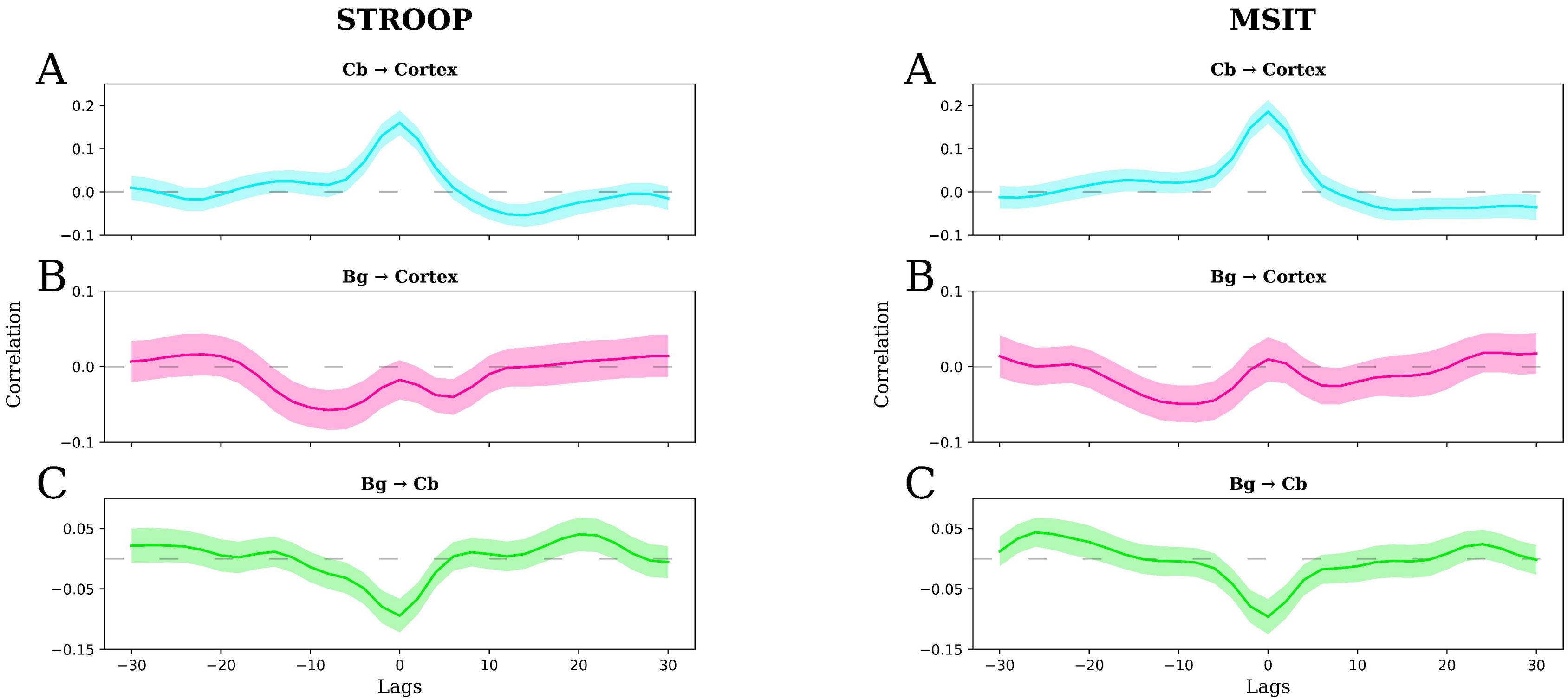
INTERPRETATION



RESULTS: AIM 2

Cross Correlation





CONCLUSION

- Cortical network topologies are highly flexible.
- Basal ganglia engagement peaks at the beginning of task blocks, while cerebellum at the end.
- Evidence for basal ganglia as a control mechanism for cortical network topology, but not cerebellum

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THANK YOU !!

Committee members

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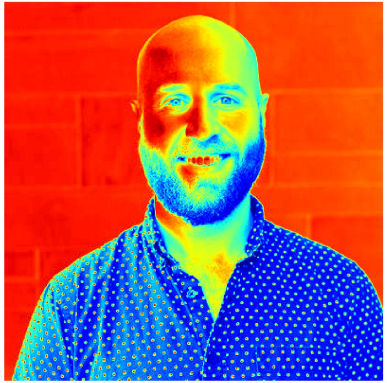

CoAx LAB

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QUESTIONS ?