Connectivity & Modelling

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Overview

Connectivity (response inhibition)

- Background
- Classical work
- Theoretical Networks
- Networks of Response inhibition - 2 cases

Cognitive Modelling (Learning)

- Background
- Theories of learning
- Neuroscience of learning
- Advances with Cognitive Modelling

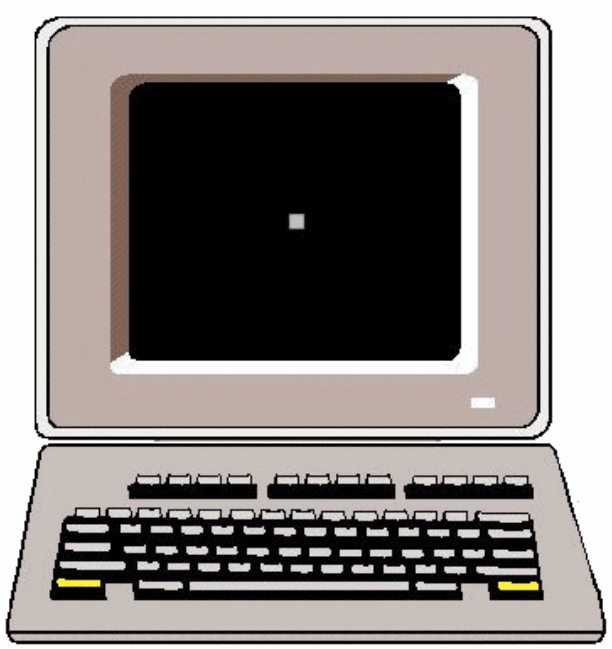
Response Inhibition

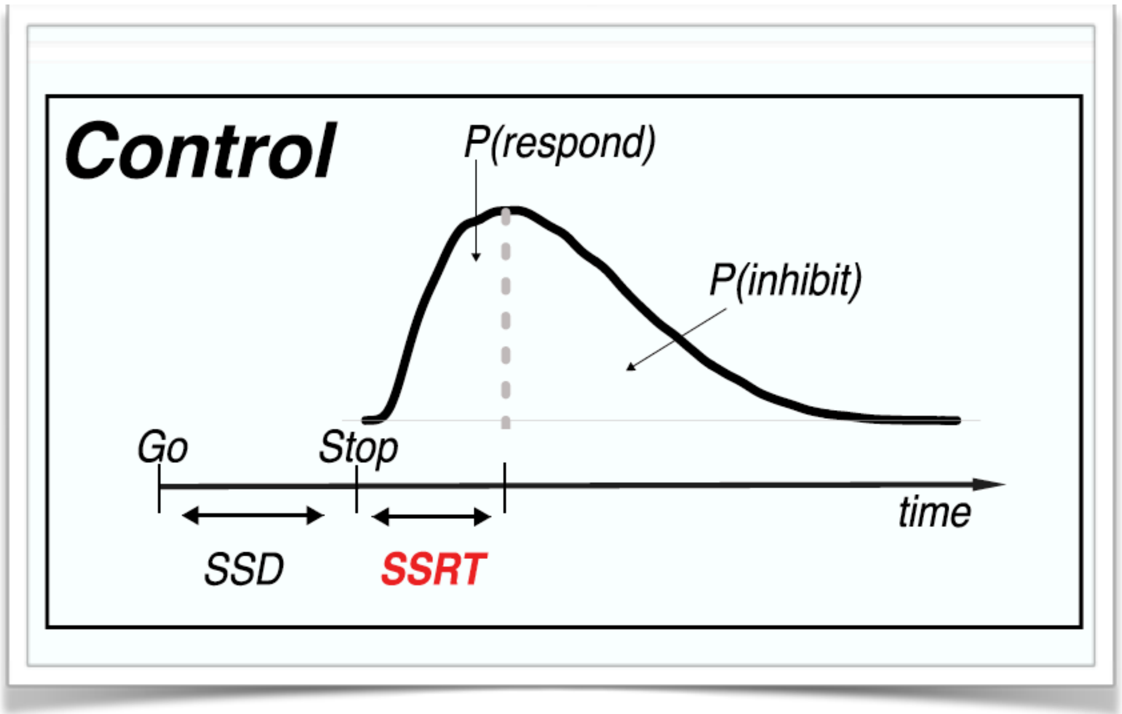
The ability to suppress prepared, automatic, or impulsive responses

The Paradigm

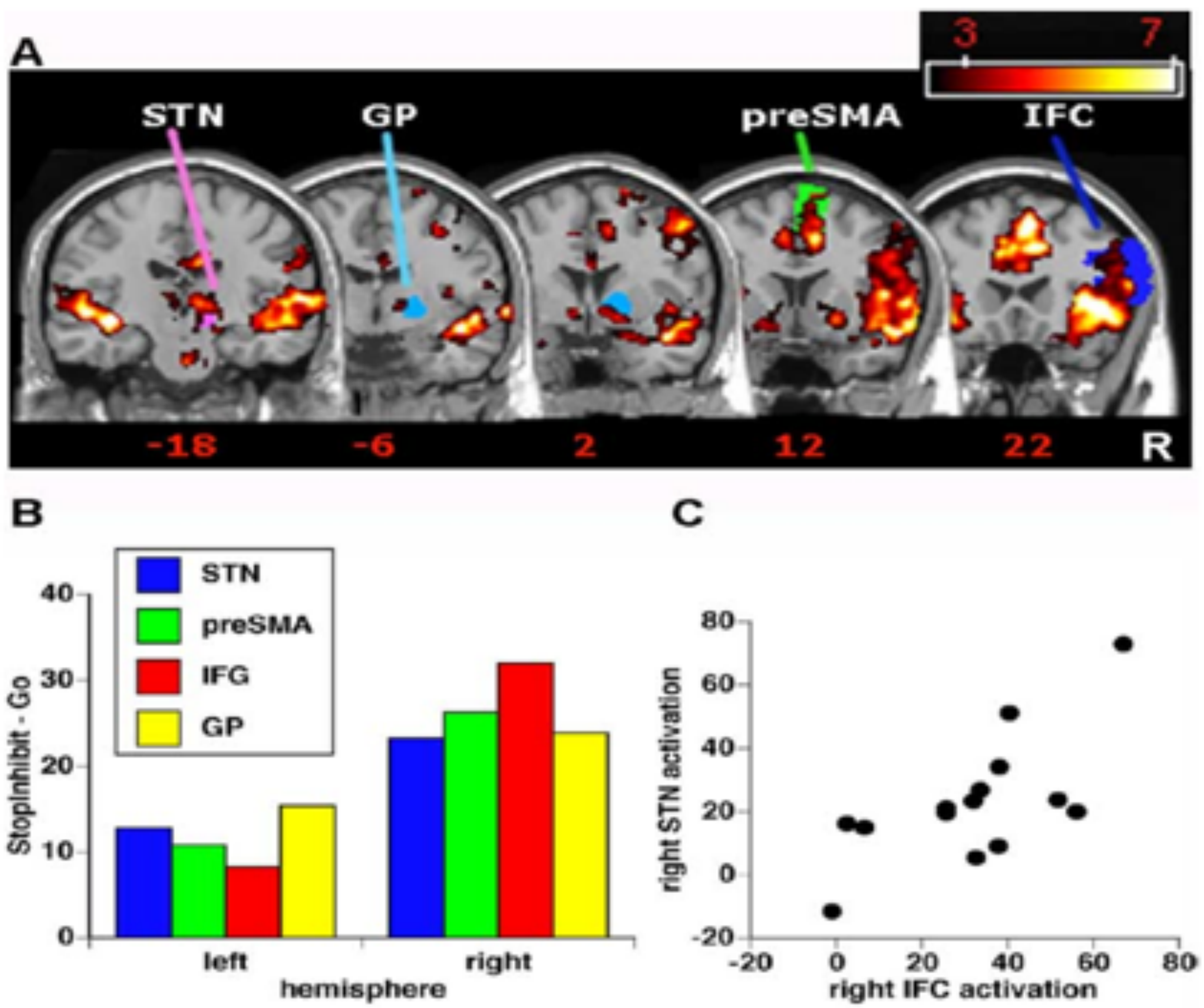
Stop signal task

- Response selection reaction times (Go RT)
- Stop signal reaction times (SSRT)



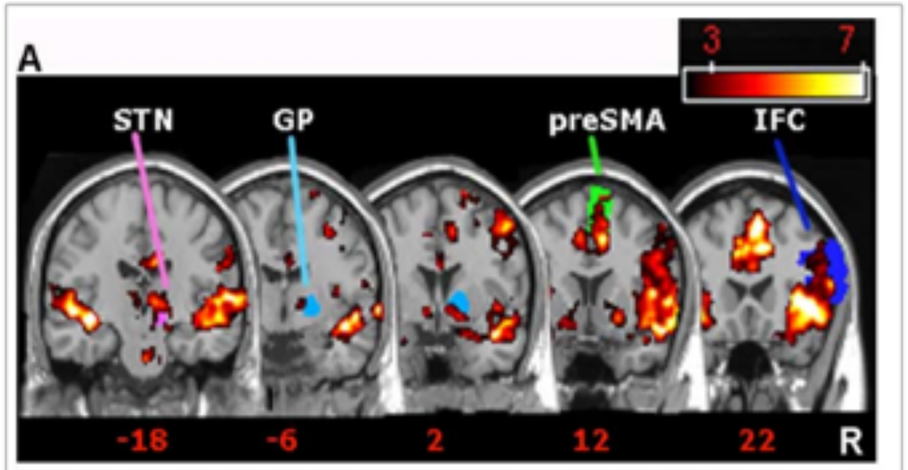


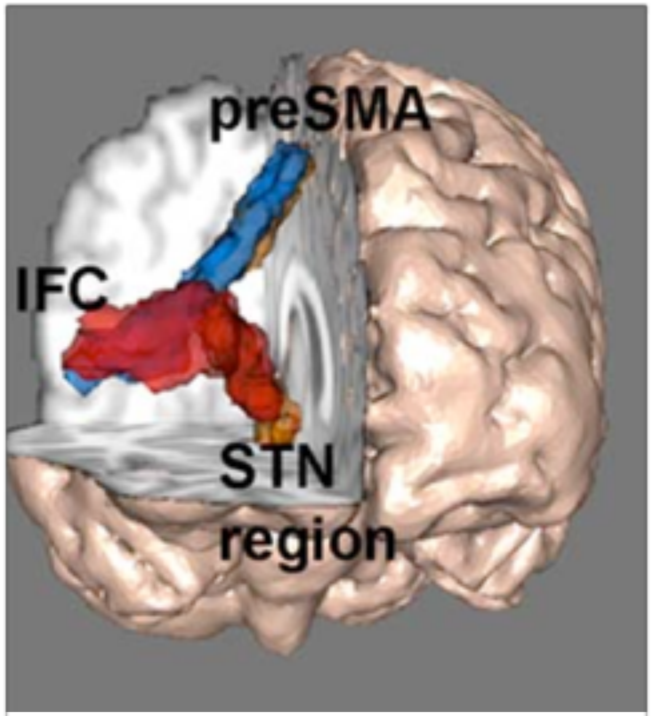
Brain and Inhibition



Aron and Poldrack (2006). *JoN*

Structure and Inhibition

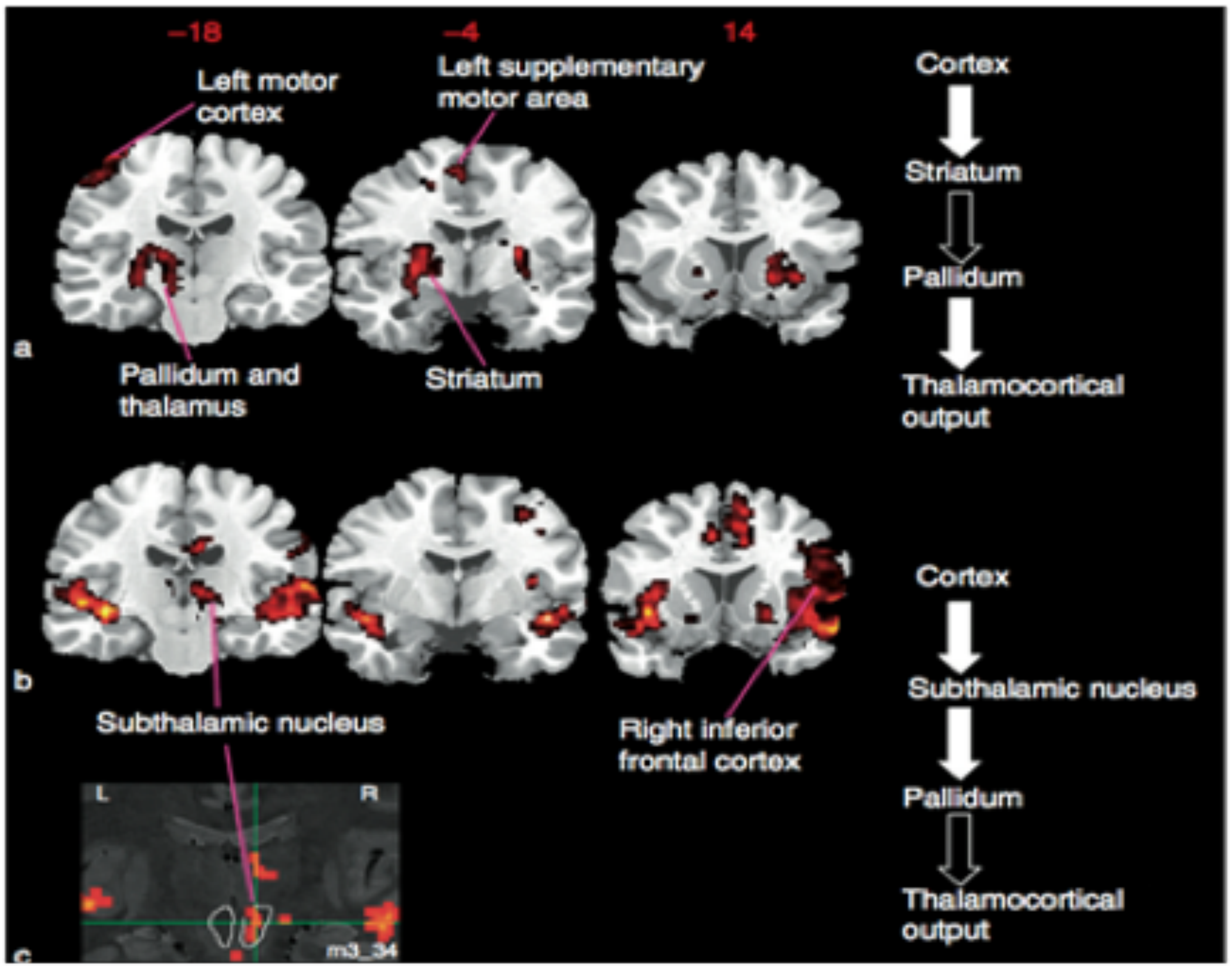




Aron et al. (2007). *JoN*

How do these regions, important for response inhibition, work together as a system to implement stopping?

Theories of connectivity

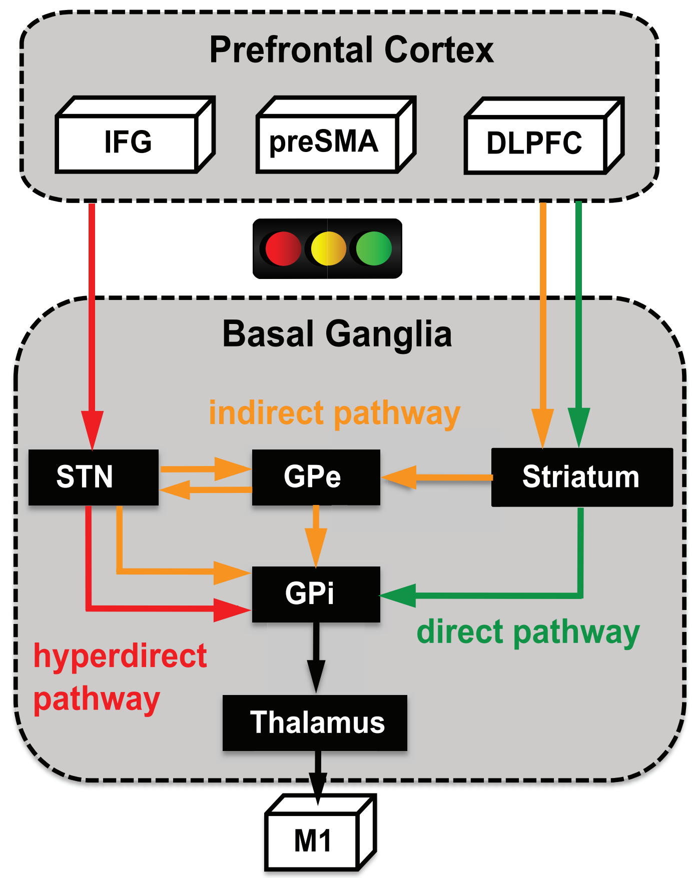


Direct Pathway

Hyper direct Pathway

Aron and Poldrack (2006). *JoN*

Theoretical Networks



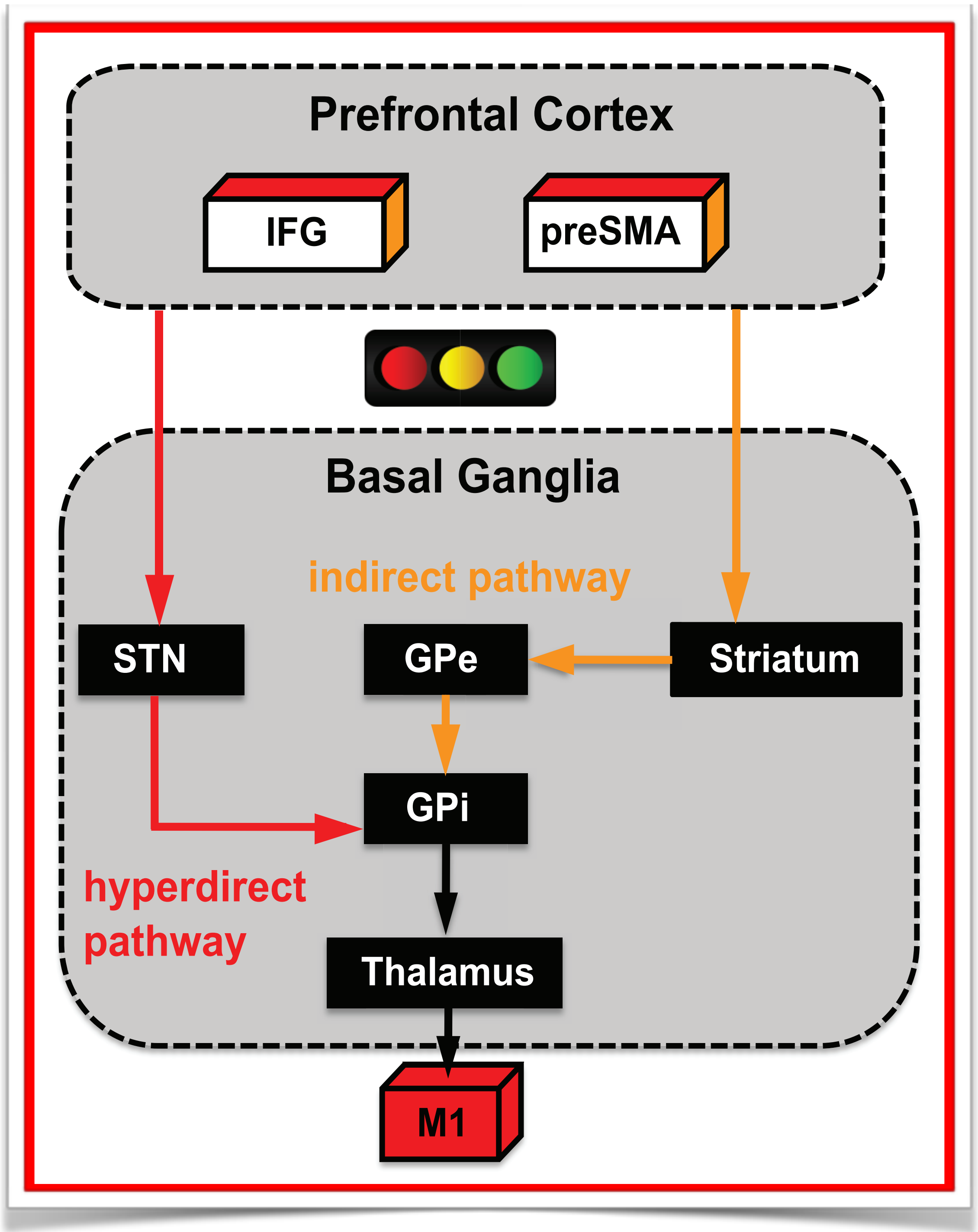
Alexander et al. (1986) *Annu Rev Neurocisce;* Mink (1996). *Prog in Neurobiology*

Connectivity study 1

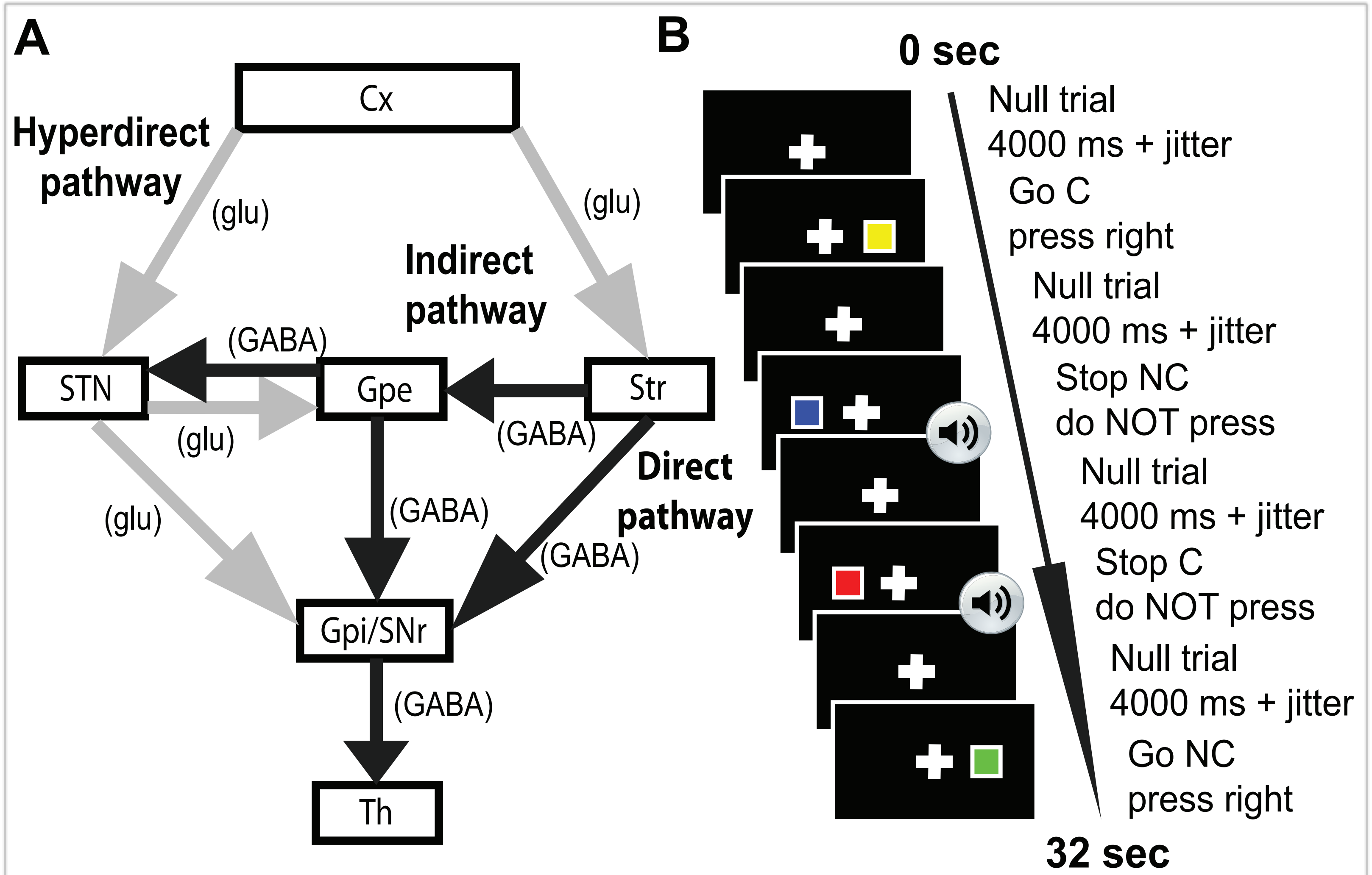
How does the brain implement response inhibition?

Jahfari et al. (2011). Journal of Neuroscience

Networks of stopping

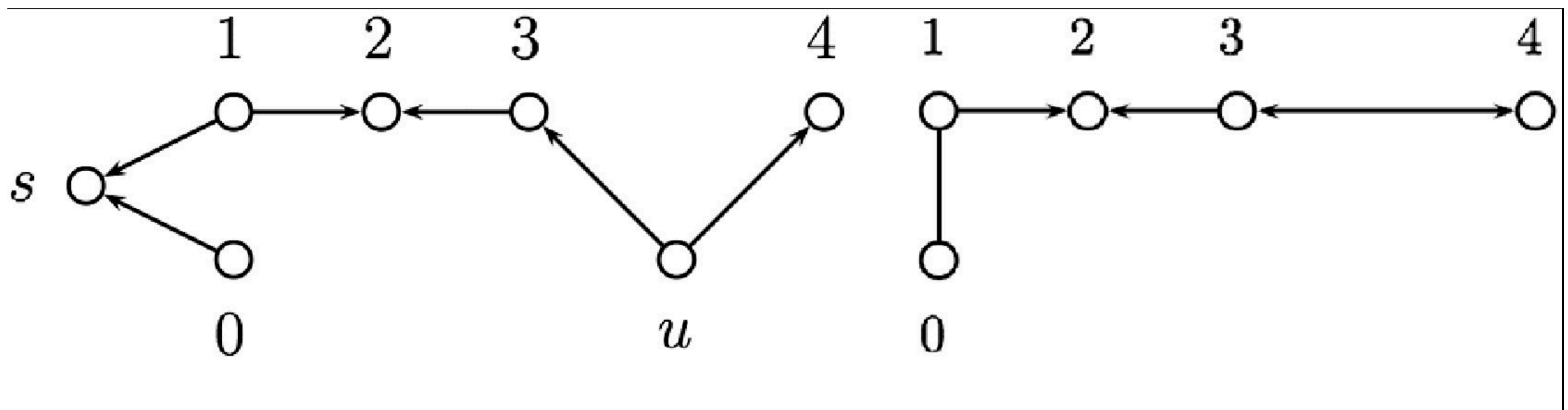


Approach

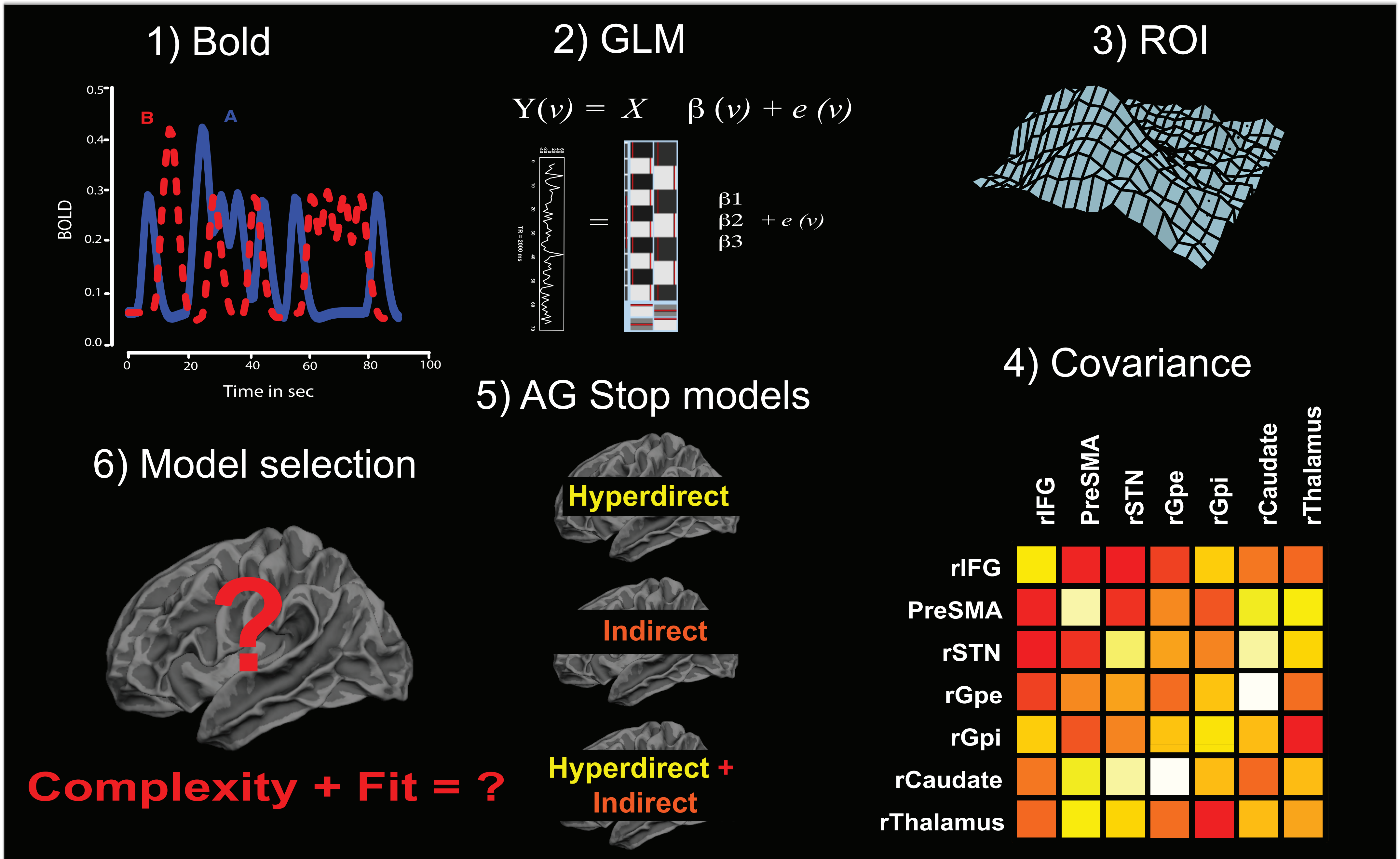


N= 20, fMRI, Task = Stop Simon

Connectivity

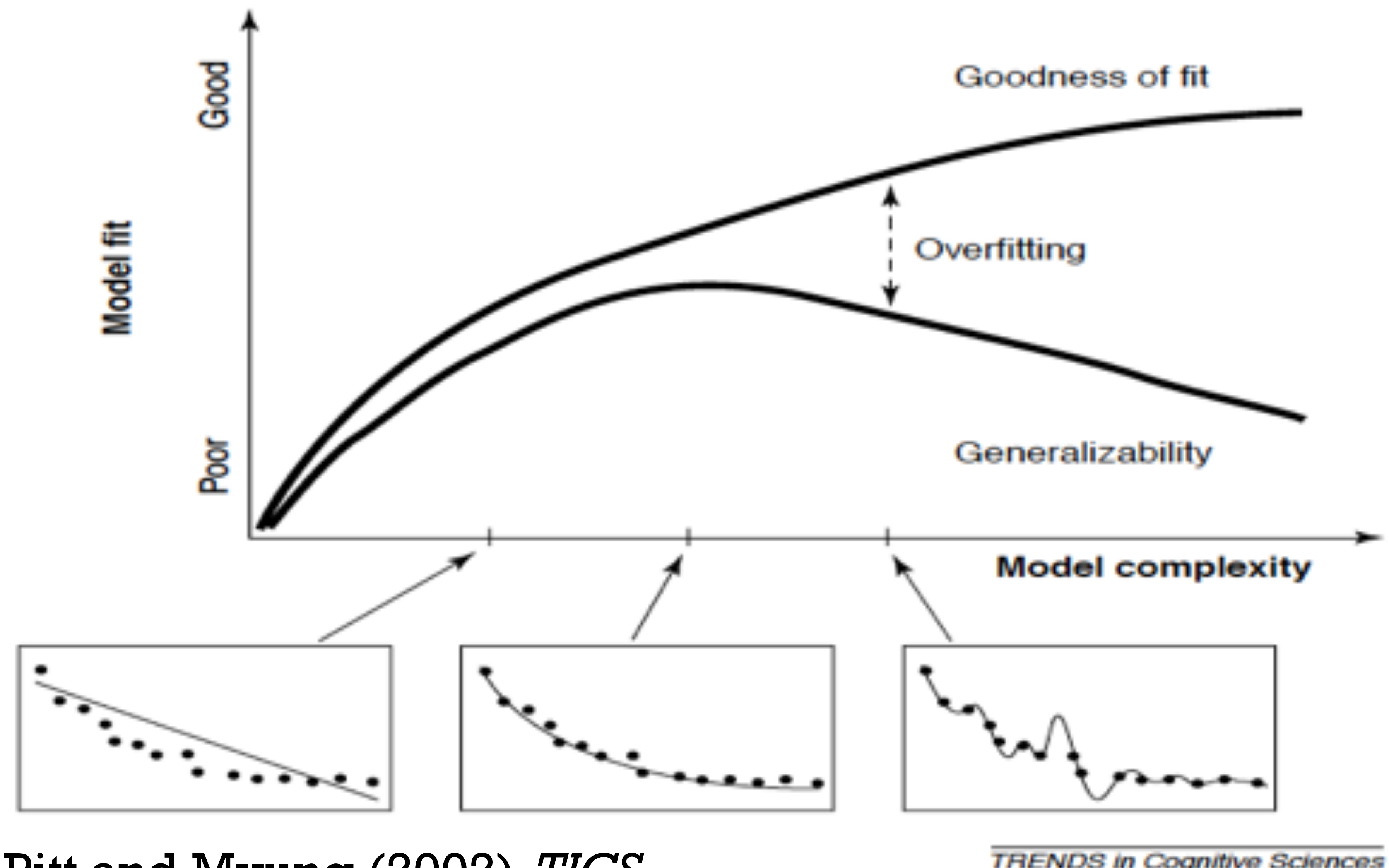


Ancestral Graphs



Waldorp et al. (2011). *NeuroImage*

Fit and Complexity



Pitt and Myung (2002). *TICS*

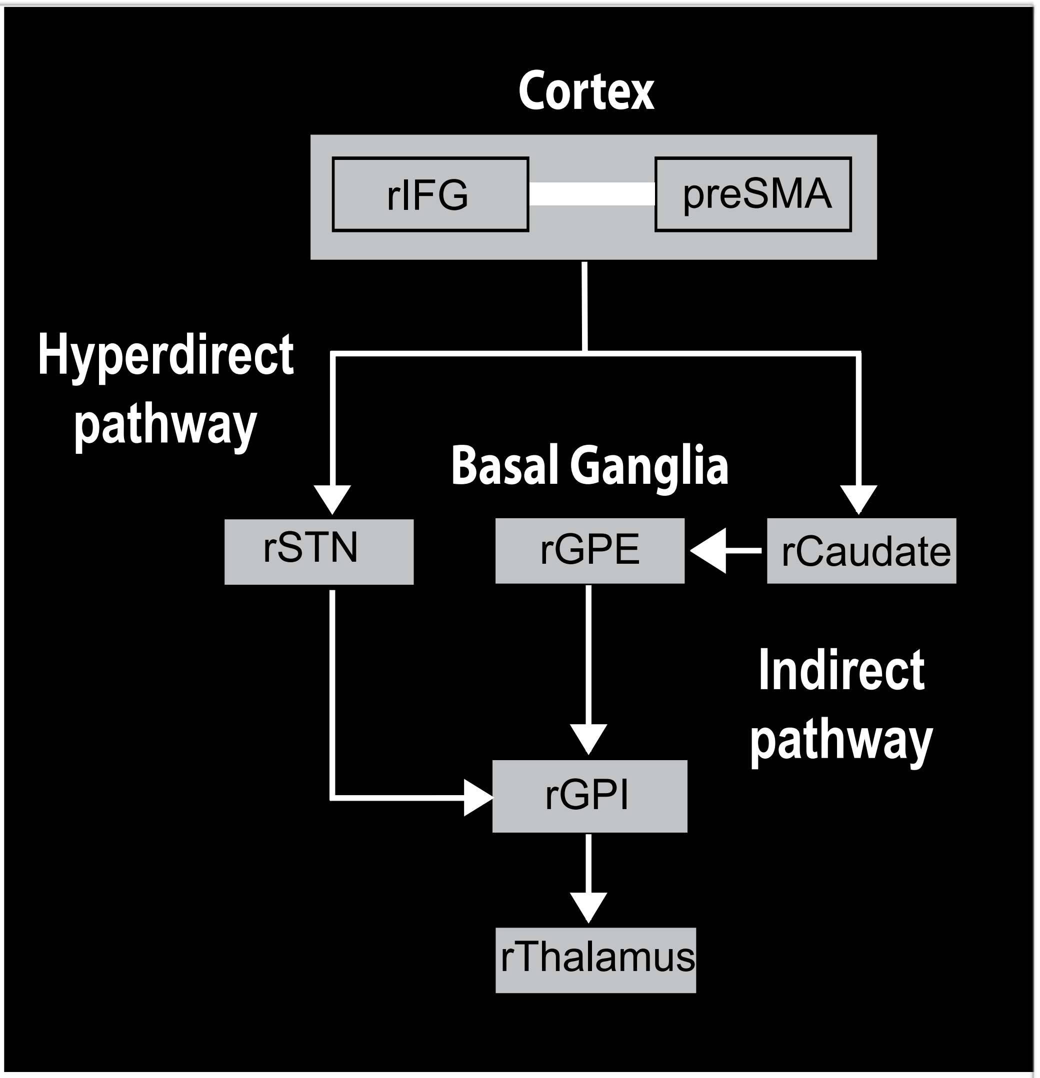
Questions

1. What is the <u>**best**</u> fronto-basal ganglia model to explain the pattern of activity in the brain during Stop trials?

2. Do the overall connection strengths of the identified model differentiate between the conditions?

The best Network

	AIC Stop Inhibit		AIC Stop Respond	
	CG	IC	CG	IC
InDirect				
rIFC	2296.2	2235.7	2223.9	2235.8
preSMA	2306.2	2261.0	2248.0	2227.0
rIFC&preSMA	1997.1	1925.1	1934.2	1918.6
Hyperdirect				
rIFC	2564.1	2469.4	2498.4	2479.0
preSMA	2561.9	2463.4	2508.1	2478.5
rIFC& preSMA	2281.4	2152.6	2215.3	2192.1
Hyper+Indirect				
rIFC	2232.6	2154.6	2155.8	2181.3
preSMA	2240.5	2174.0	2189.6	2171.9
rIFC& preSMA	**1903.1**	**1792.4**	**1850.9**	**1839.4**

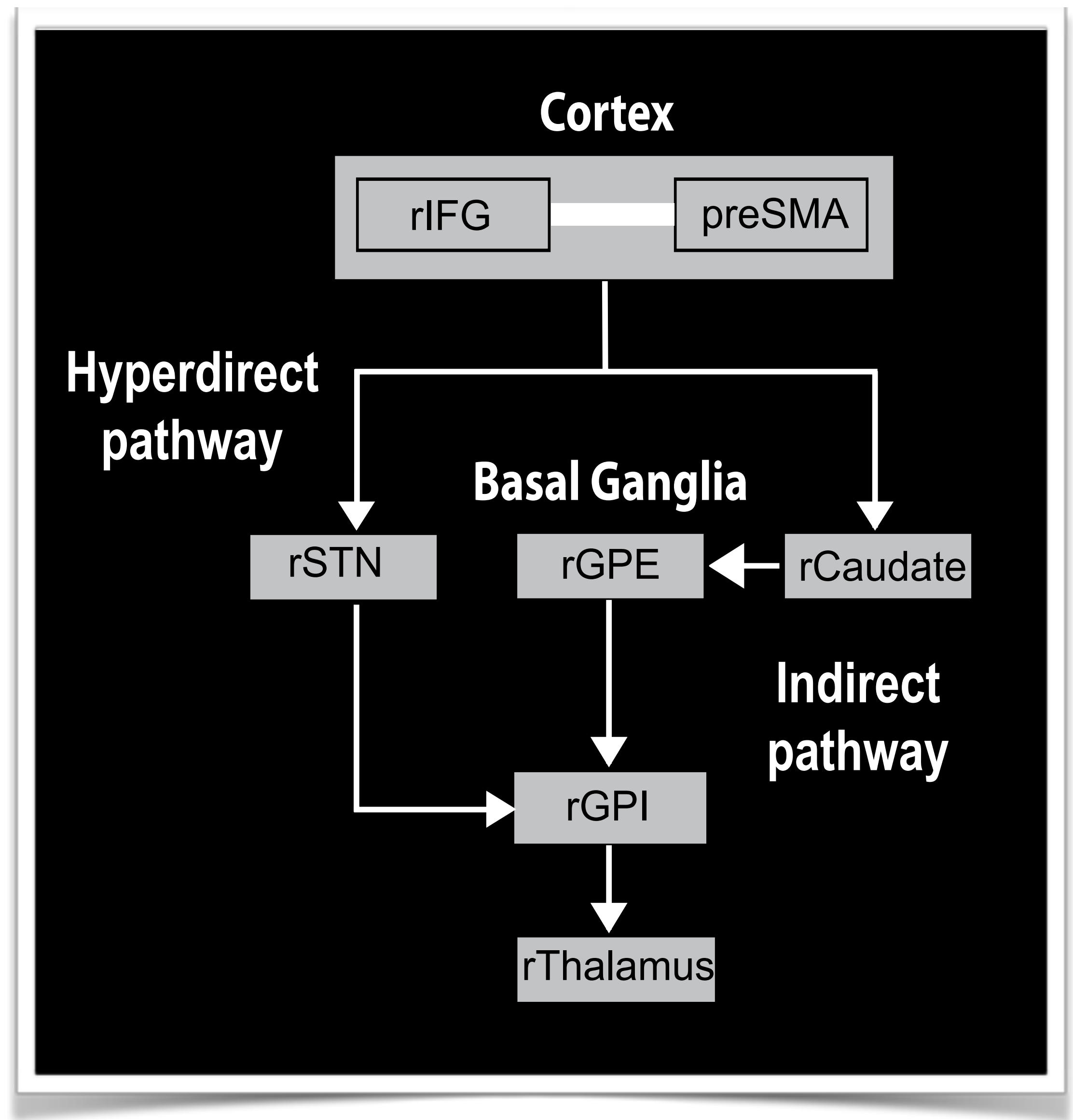


Differentiation

Overall connection strength

Successful Stop > Failed Stop

No effect for congruency



Conclusions

Findings from this experiment infer:

An informative model to explain the pattern of activity during stop trials!

- Both the hyperdirect and indirect fronto-basal ganglia pathway play a crucial role during response inhibition.

Informative differences between conditions!

- Stronger overall model connections were observed for successful stops.

Meaningful information from individual differences!

- Especially fronto-basal ganglia connections were predictive for the efficiency to withdraw a response

What else?

Connectivity study 2

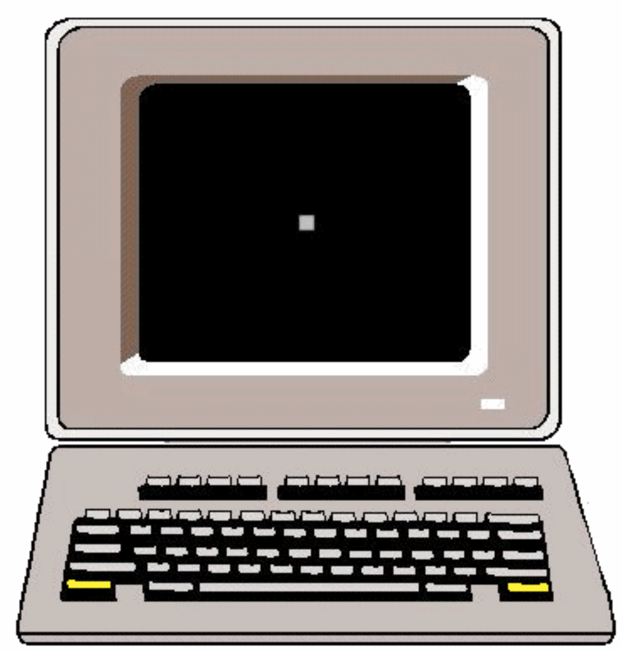
Top-down modulations in networks of response inhibition

Jahfari et al. (2012). Journal of Neuroscience

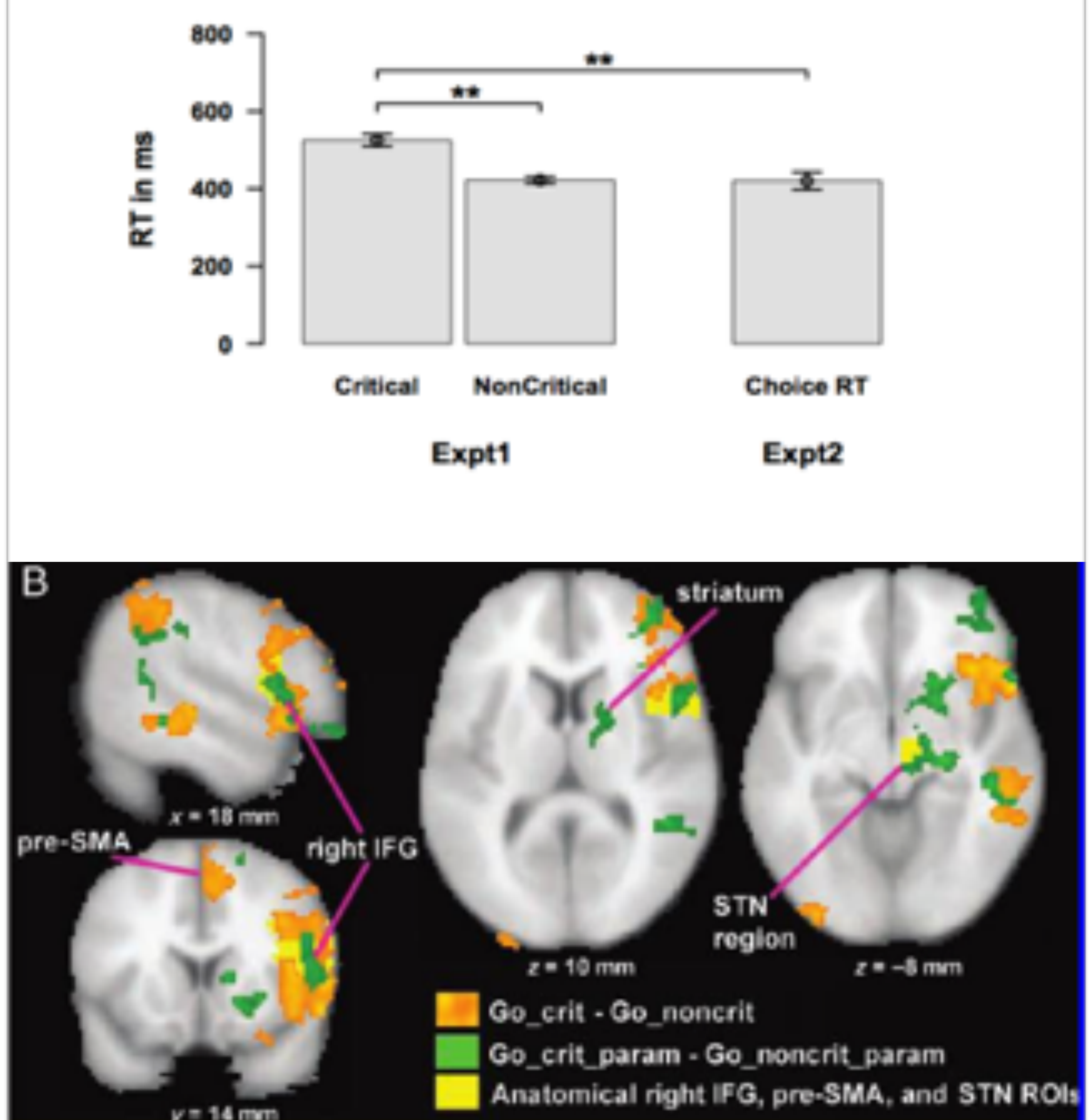
Proactive Control

Conditional Stop task

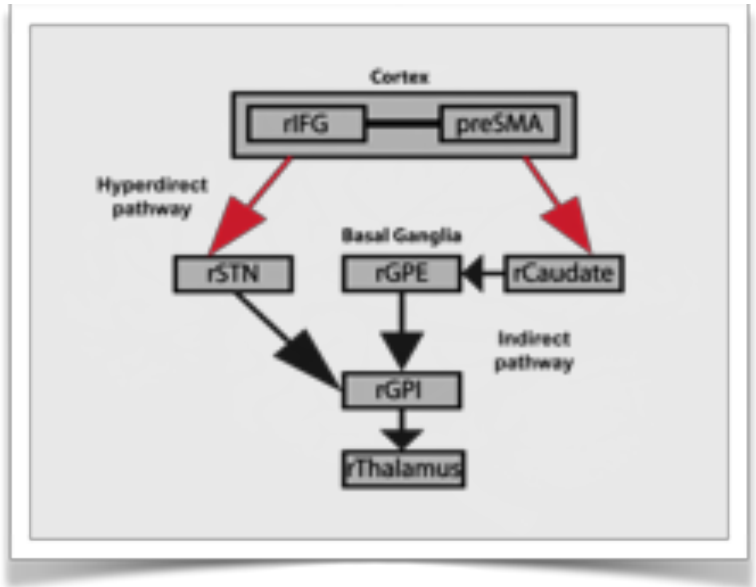
- Only stop when the stop-signal follows an arrow point to the right (critical Go).



Proactive Control



Jahfari et al. (2010). *JoCN*

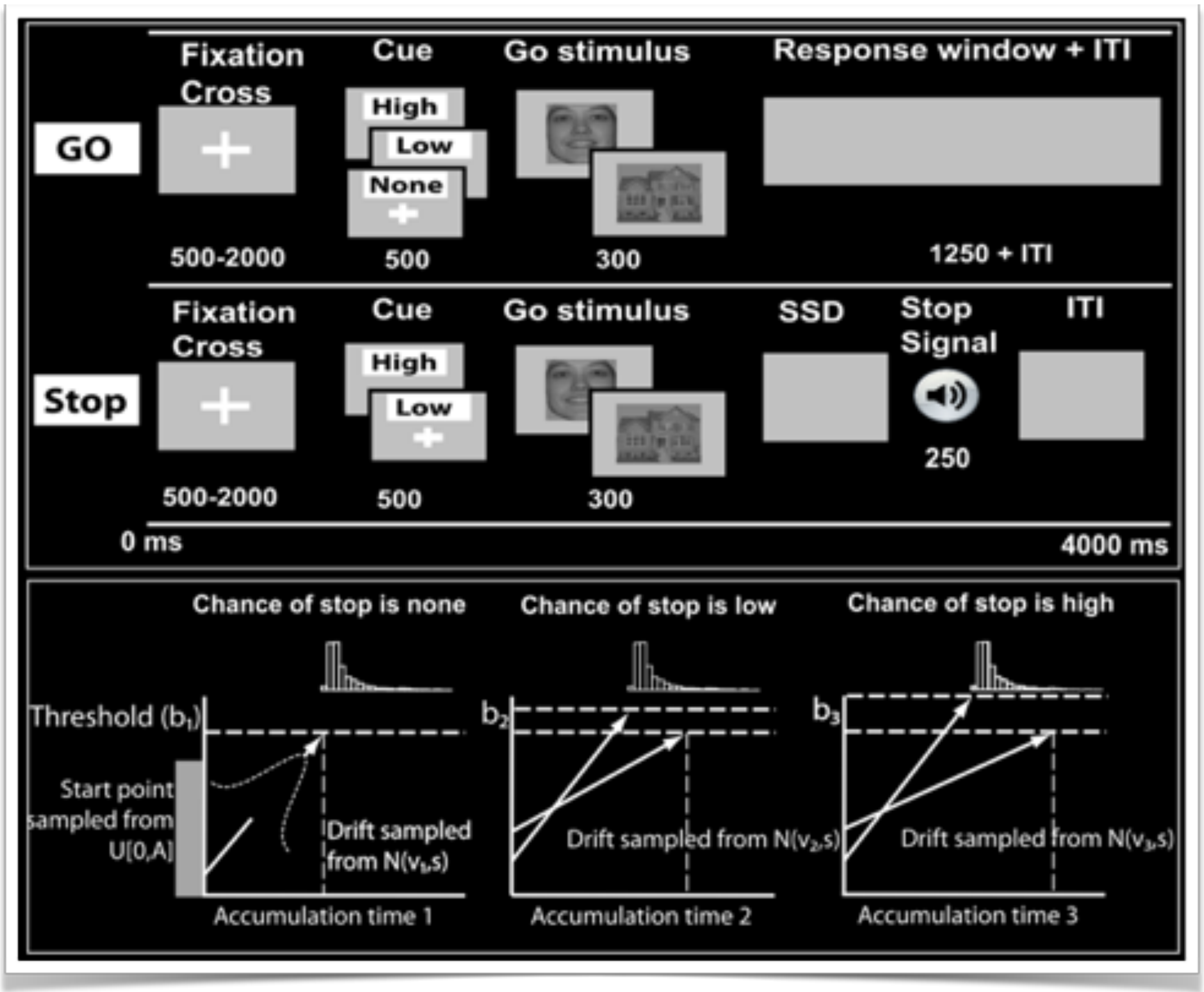


Question

Are fronto-subcortical connections important for inhibition modulated by the level of proactive control?

Jahfari et al. (2012). Journal of Neuroscience

Approach


Fixation Cross
Cue
Go stimulus
Response window + ITI
GO
High
Low
None
500-2000
500
300
1250 + ITI
Fixation Cross
Cue
Go stimulus
SSD
Stop Signal
ITI
Stop
High
Low
250
500-2000
500
300
0 ms
4000 ms
Chance of stop is none
Chance of stop is low
Chance of stop is high
Threshold (b_1)
b_2
b_3
Start point sampled from U[0,A]
Drift sampled from N(v_1,s)
Drift sampled from N(v_2,s)
Drift sampled from N(v_3,s)
Accumulation time 1
Accumulation time 2
Accumulation time 3

Questions

Replication

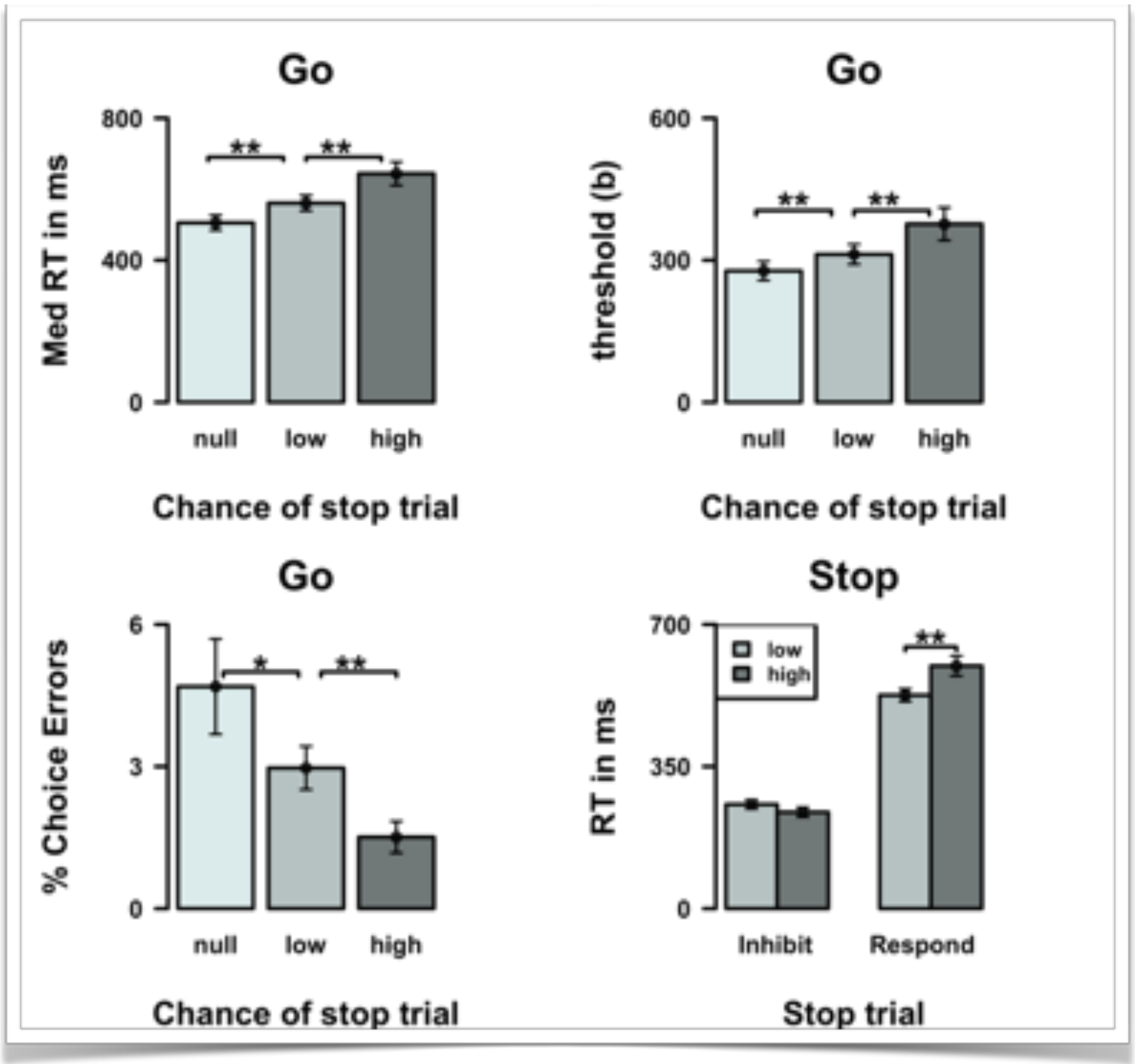
- Is the hyper-indirect network again the best model to explain activation patterns during stop trials?

Prediction

- The recruitment of the stop-network during the Go trials is tailored to the likelihood of stop trial occurrence.

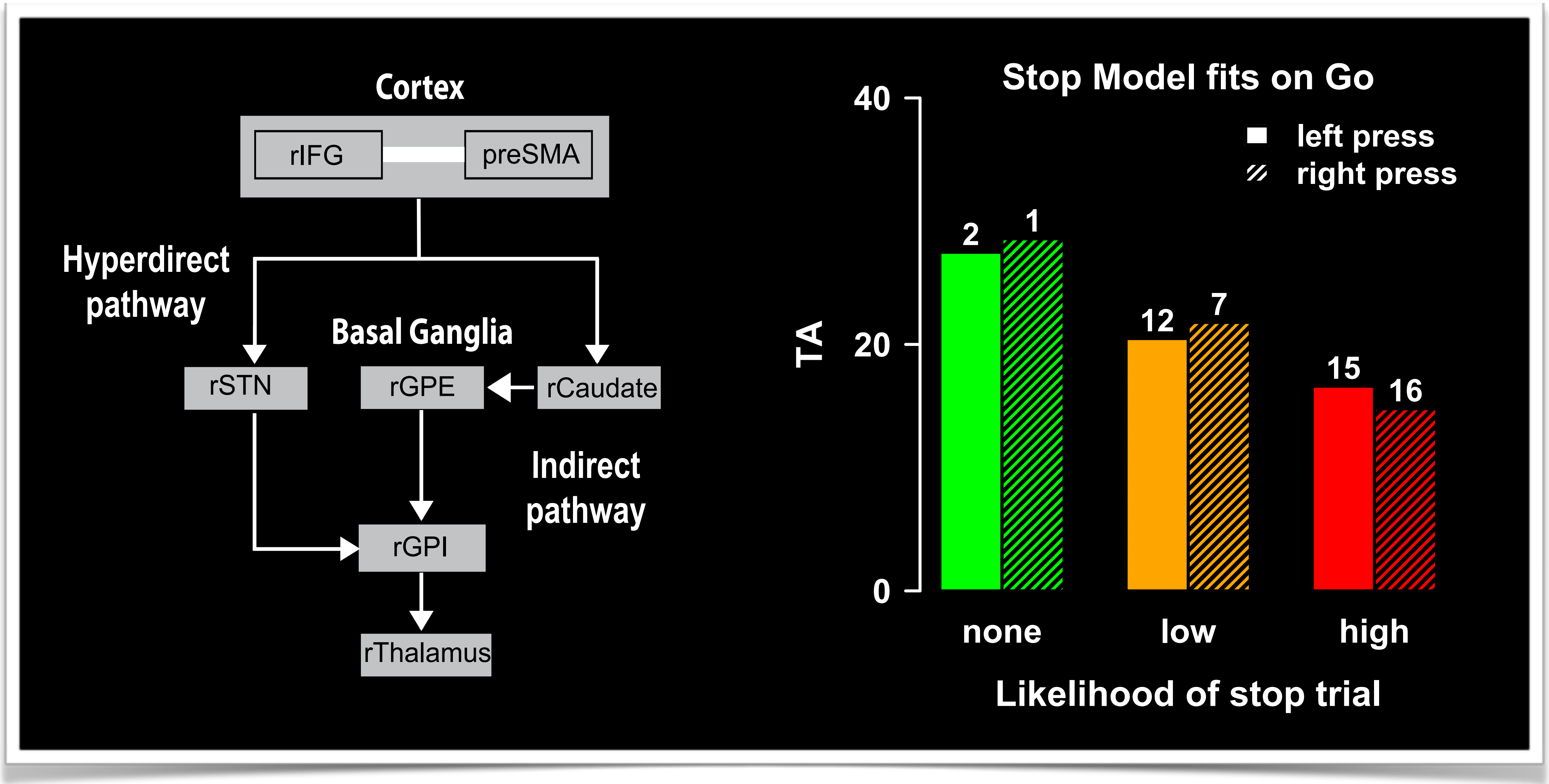
- For stopping, top-down control is expected to be weaker when participants have already proactively recruited the stop network during the go.

Behavior

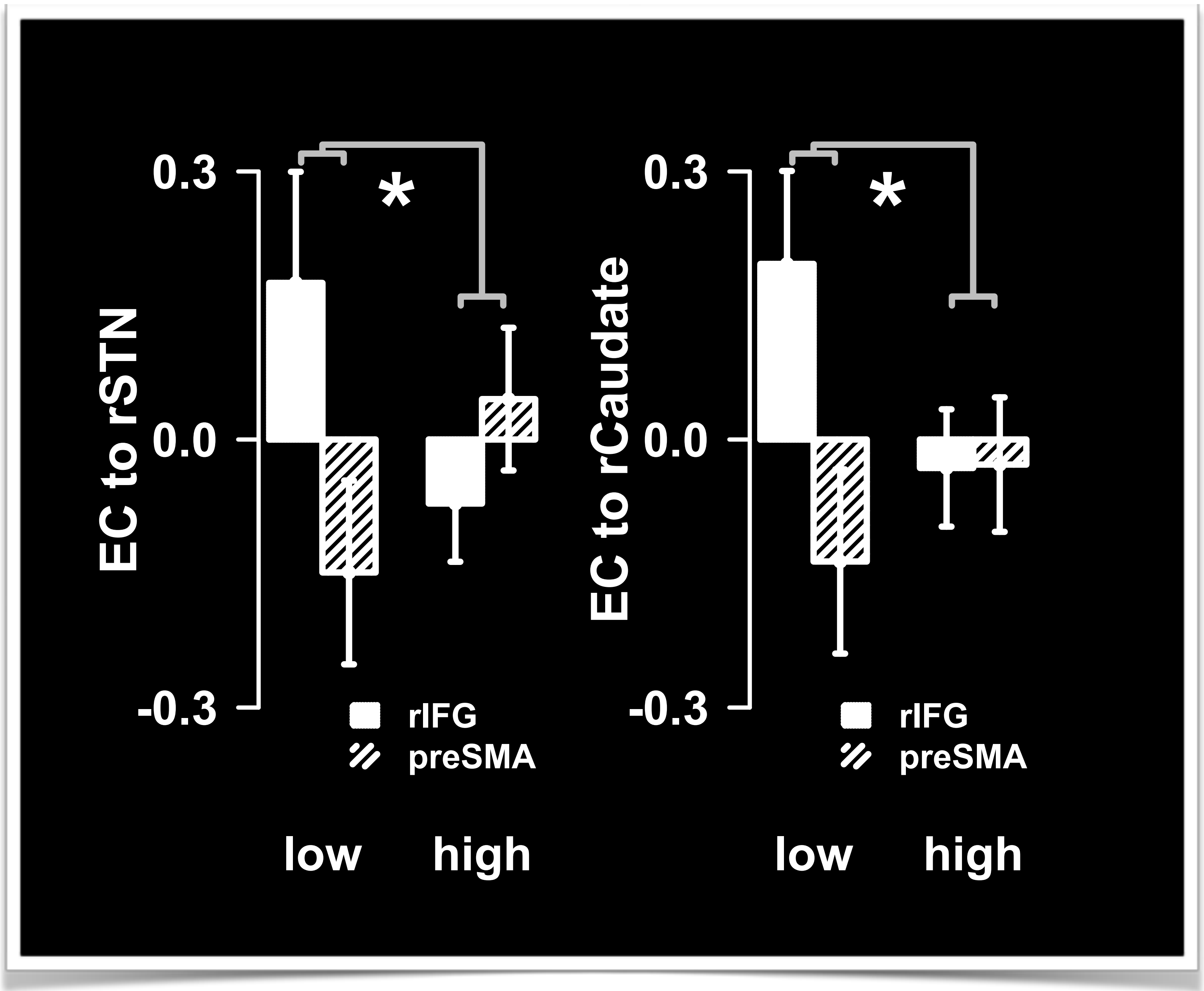


Go
800
400
0
Med RT in ms
**
**
null
low
high
Chance of stop trial
Go
600
300
0
threshold (b)
**
**
null
low
high
Chance of stop trial
Go
6
3
0
% Choice Errors
*
**
null
low
high
Chance of stop trial
Stop
700
350
0
RT in ms
low
high
**
Inhibit
Respond
Stop trial

Inhibitory Network



Top-down Modulation



Conclusions

Findings from this experiment

- **Replicate** previous findings with ancestral graphs:The Hyper Indirect model was again most representative to explain stop pattern activity.
- The full stop network is recruited during go trials with the increasing chance of a stop trial
- Top-down control from the cortex into the basal ganglia is stronger for rejecting the default (go), when stopping is reactive (chance of stop trial is low).

Cognitive Modelling

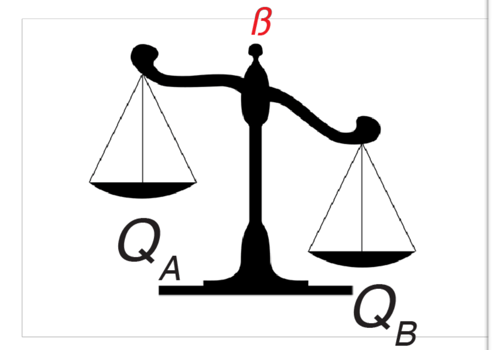
Learning

Associative learning

Theories of Learning

Relative Value and Choice

$$P_A(t) = \frac{\exp(\beta \times Q_t(A))}{\exp(\beta \times Q_t(B)) + \exp(\beta \times Q_t(A))}$$



$$\Delta \text{ Value} = \text{chosen value } (Q_A) - \text{unchosen value } (Q_B)$$

Choice and Value evaluation

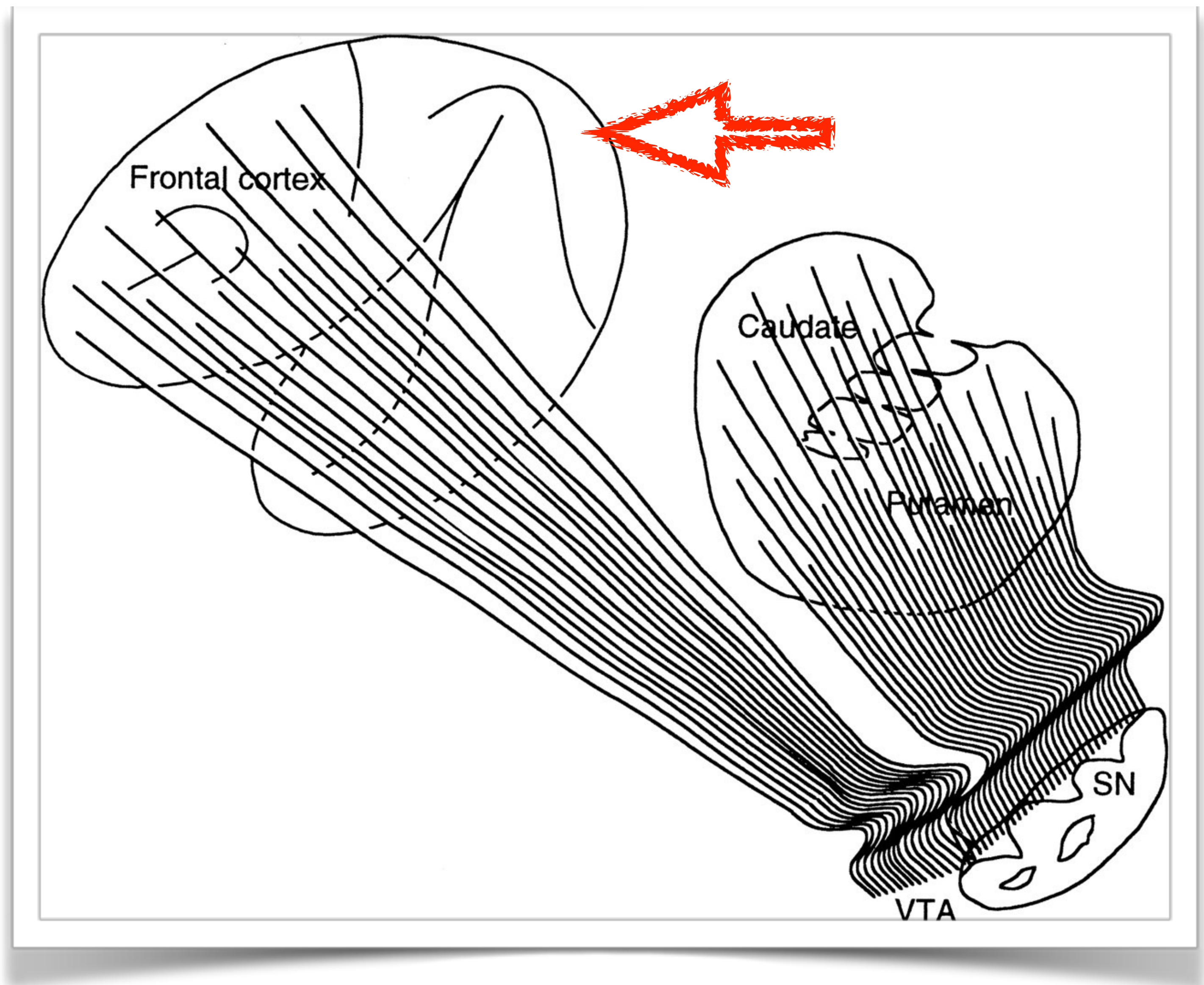
$$Q_i(t+1) = Q_i(t) + \begin{cases} \alpha_{Gain}\,[reward_i(t) - Q_i(t)], & \text{if } r = 1 \\ \alpha_{Loss}\,[reward_i(t) - Q_i(t)], & \text{if } r = 0 \end{cases}$$

Positive RPE

Negative RPE

The Neuroscience part

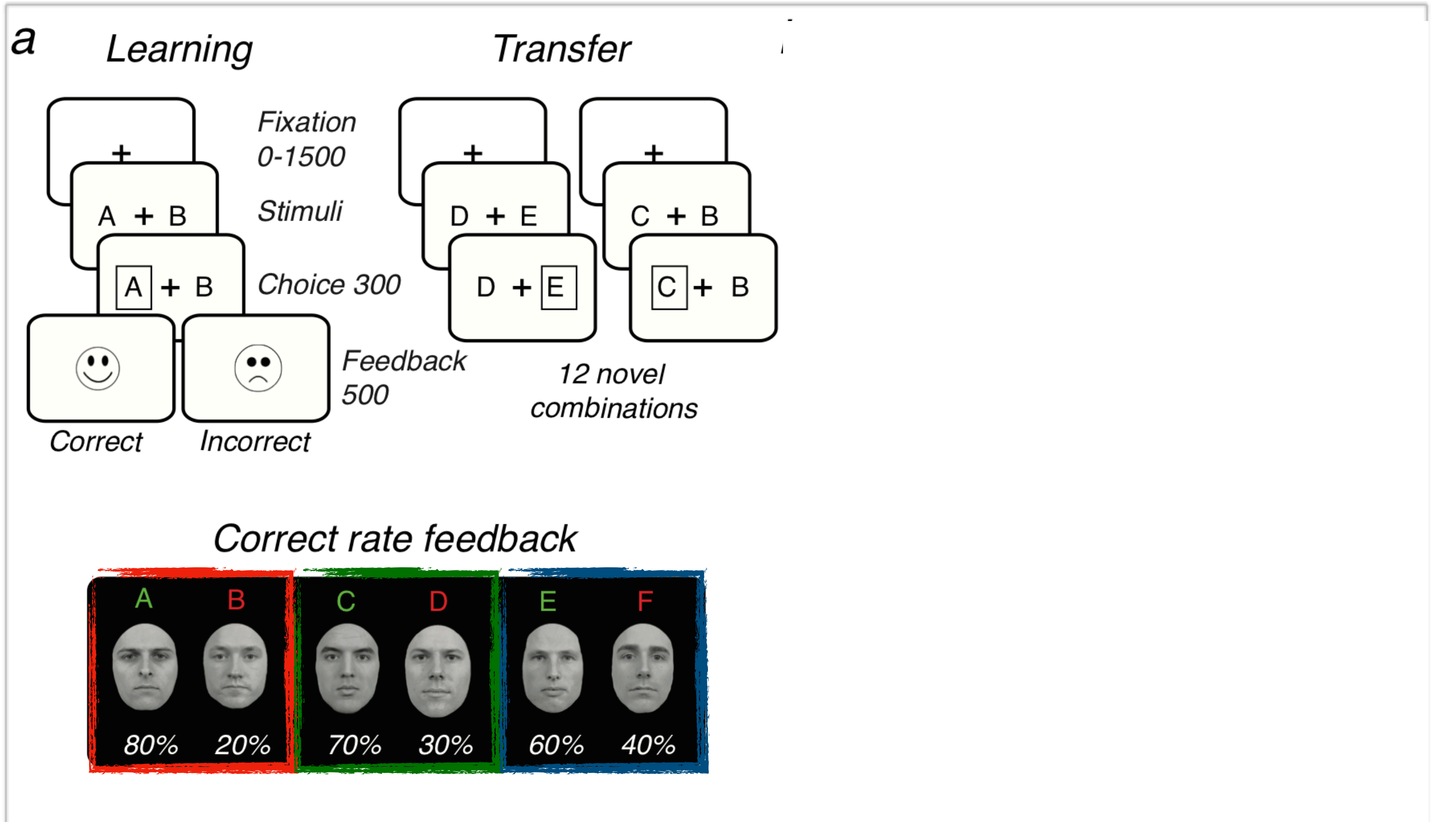
Comparison of value
Evaluation of outcomes



e.g., Daw et al. 2006, Hare et al. 2011,
O'Doherty et al. 2004, 2017,
Schultz et al.1997, 2017

Primates heavily rely on perceptual input to guide choices

How?



Jahfari et al. 2018, Cerebral Cortex

Questions

Learning phase

1. How does the BOLD response in the perceptual regions (i.e., FFA, Occipital Cortex) relate to the 'online' tracking of

   - Value beliefs about the face options presented

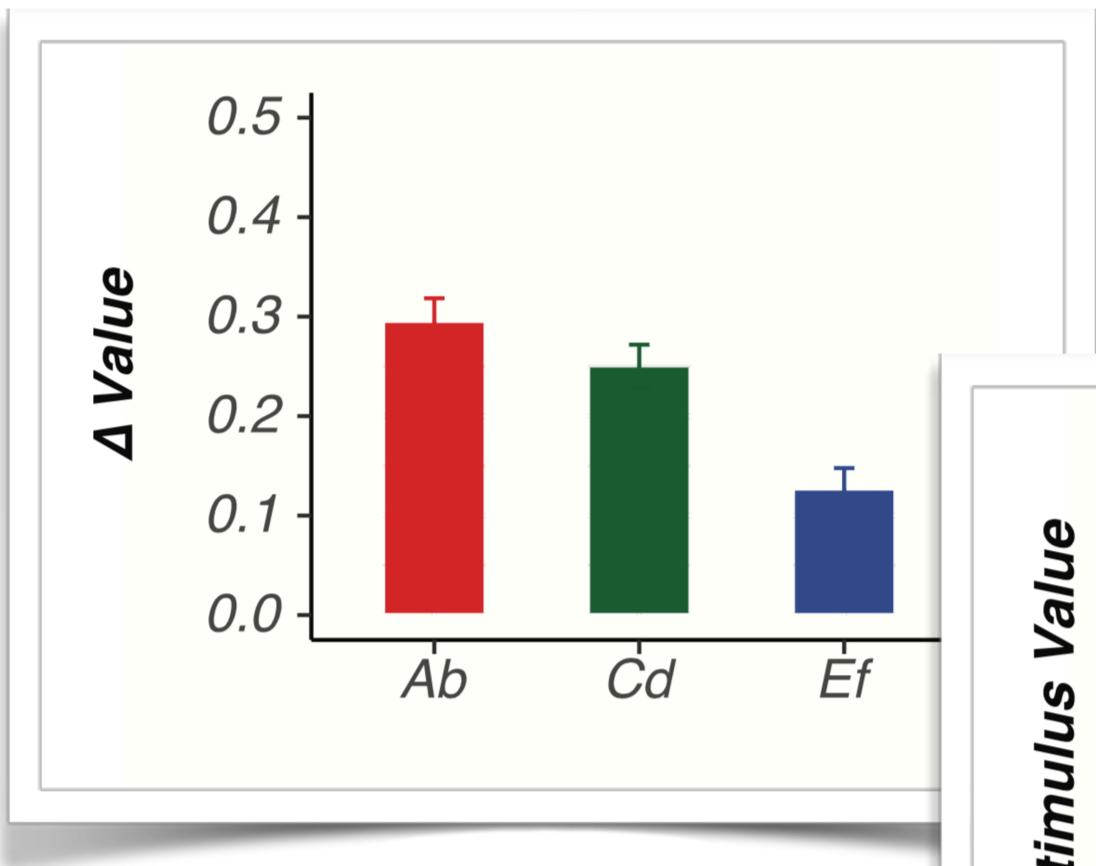
   - The evaluation of choice outcomes.

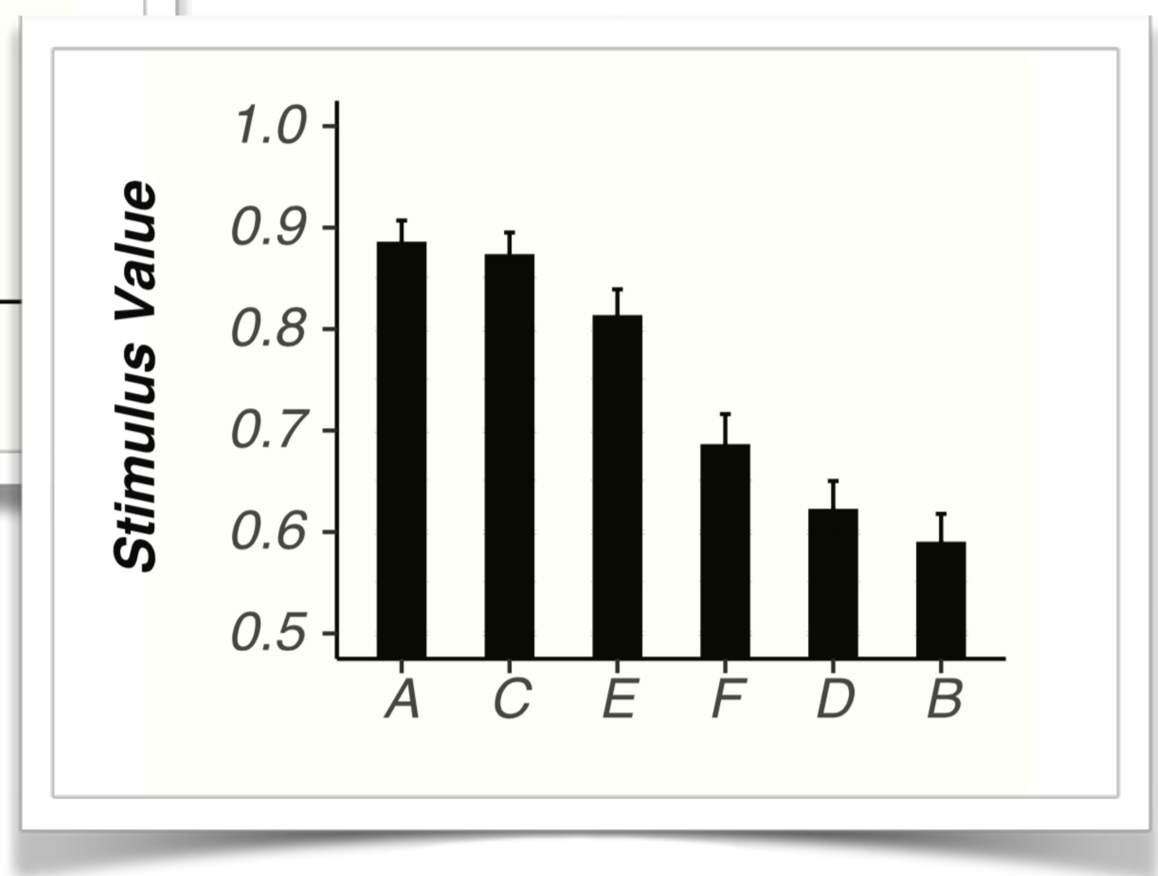
Transfer phase

2. What is the importance of perceptual regions in the prediction of future value-based decisions.

Jahfari et al. 2018, in prep

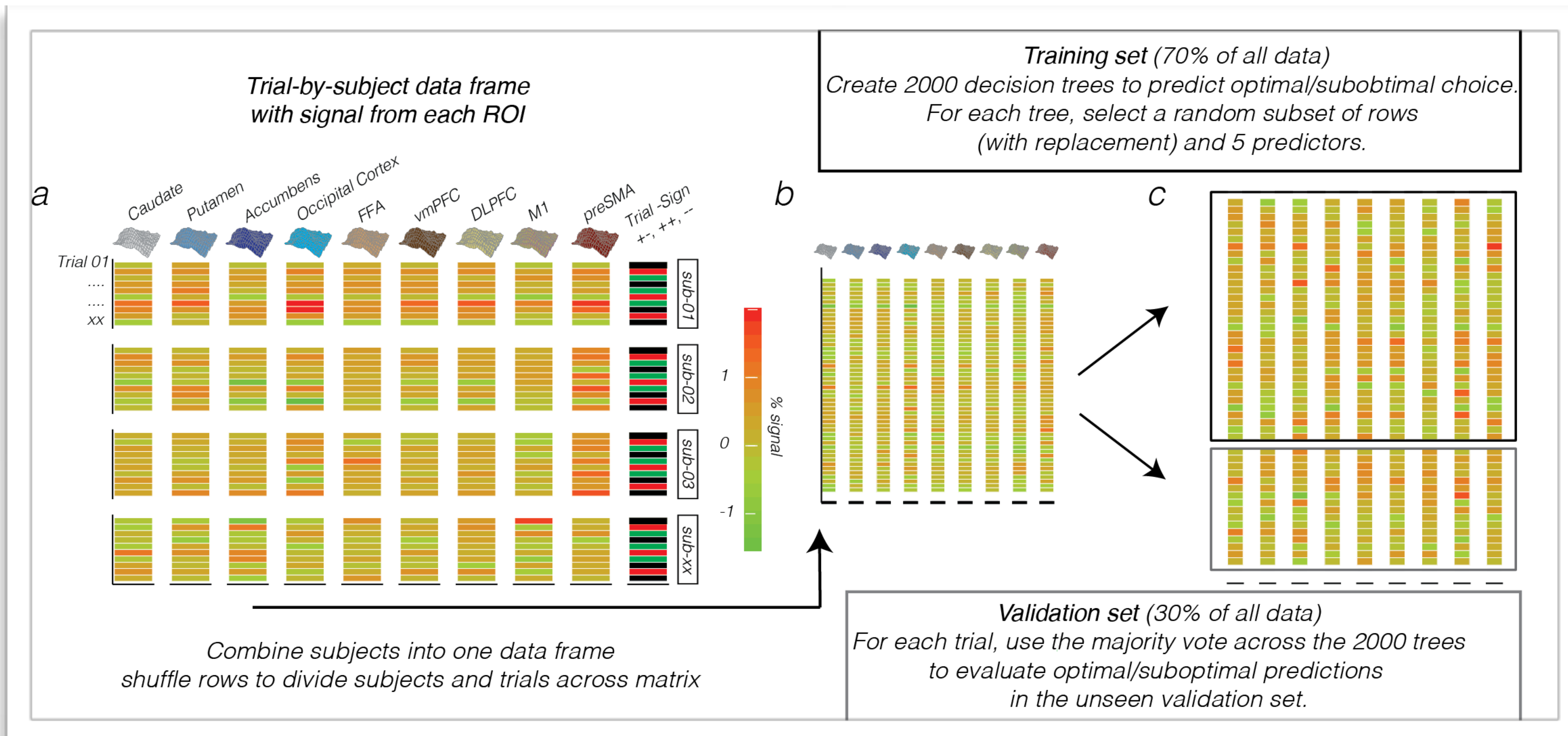
Behavior





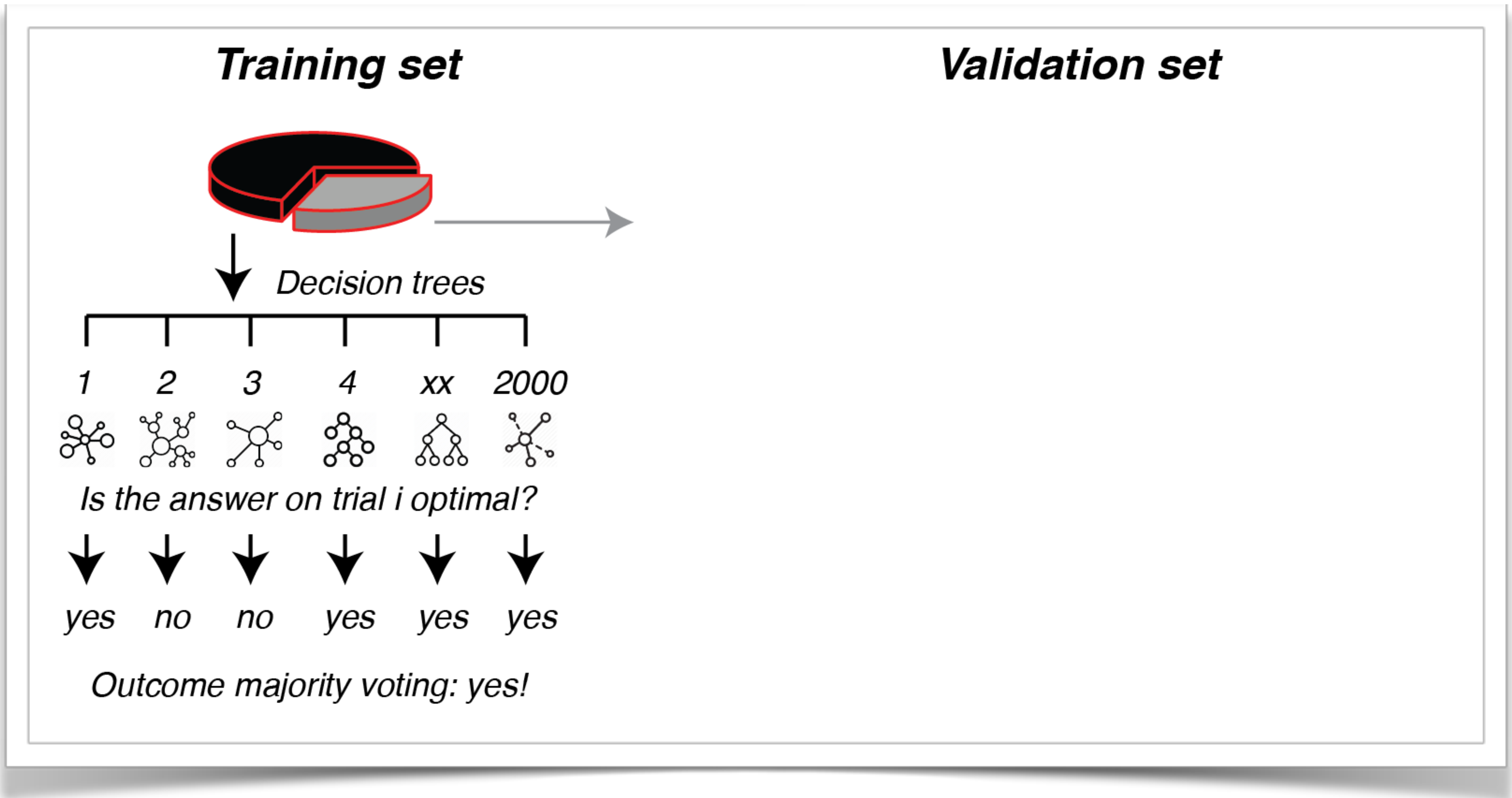
Jahfari et al. 2018, in prep

Prediction of value-driven choice with Random Forest



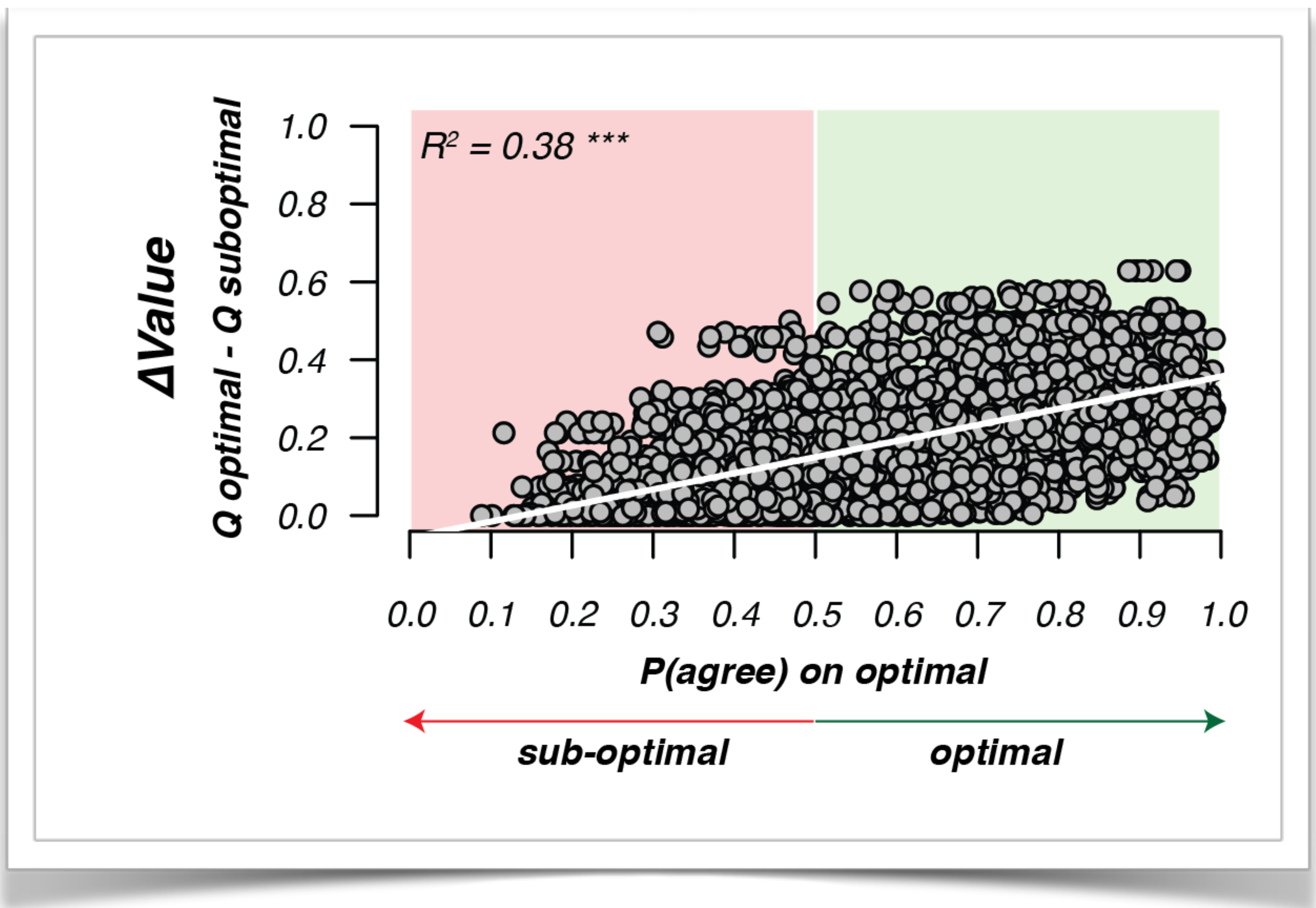
Jahfari et al. 2018, in prep

Prediction of value-driven choice



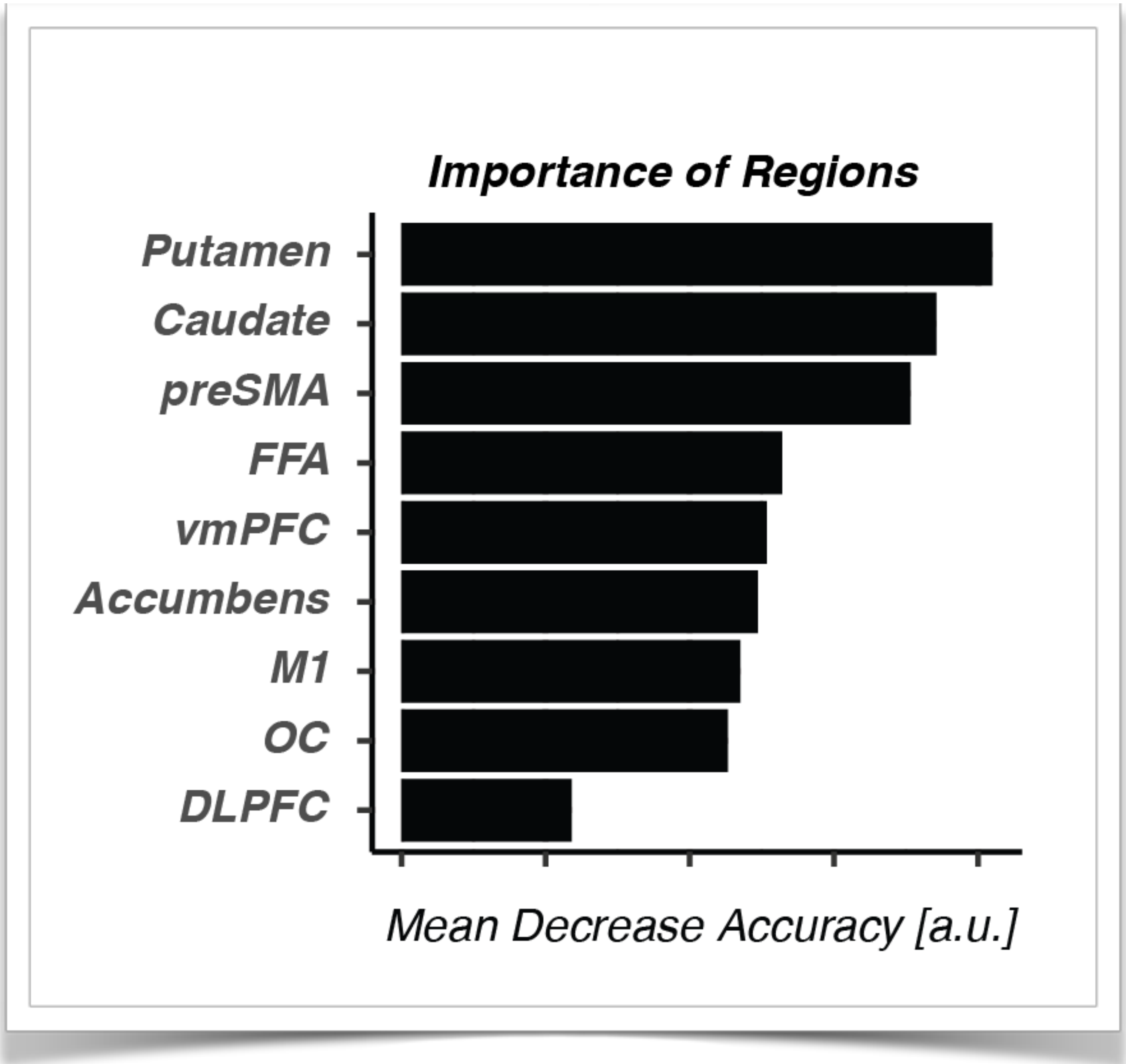
Jahfari et al. 2018, in prep

Prediction of value-driven choice



Jahfari et al. 2018, in prep

Ranking of regions



Jahfari et al. 2018, in prep

Summary

Findings

- RF model using single-trial BOLD to predict future value-driven choices.
    - Predictions improved for good learners
    - The uncertainty of predictions was related to value differences
- The FFA ranked just after the dorsal striatum, and preSMA

Prospect

- Cognitive models can increase our interpretation of Neuroscience results
- Provide new perspectives to aks new questions

Connectivity and Modelling

Questions?

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