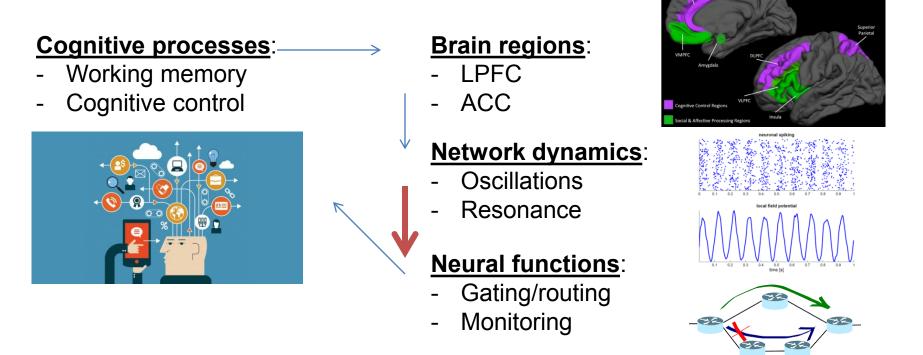
Prefrontal rhythms for cognitive control

Jason Sherfey PhD Defense at Boston University 30-Mar-2017

Approach

Overarching goal: Understand how frontal cortical network oscillations contribute to cognition.



Approach:

- Build models constrained by anatomy and physiology of relevant brain circuits.
- Use computational modeling to study the functional implications of network dynamics observed during cognitive tasks.

Outline

1. Background

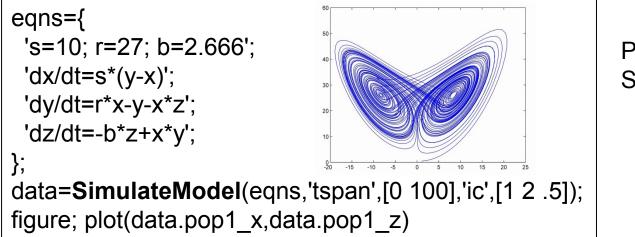
- 1. <u>DynaSim</u>: a modeling tool
- 2. Cognitive processes and related brain regions/dynamics
- 3. Neural dynamics (oscillations and resonance)
- Prefrontal rhythms for cognitive control: <u>pathway selection</u> (gating and rule-based S→R mapping)
- 3. Prefrontal rhythm control (rule selection)
- 4. ACC heterogeneity for <u>combinatorial processing</u> (evaluation for regulating cognitive control)

Background

DynaSim – MATLAB Toolbox for Modeling and Simulation

www.GitHub.com/DynaSim

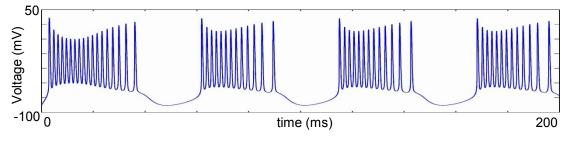
Example: Lorenz equations:



Pass equations directly to SimulateModel.

Example: Hodgkin-Huxley-type bursting neuron:

eqns='dv/dt=5+@current; {iNaF, iKDR, iM}; v(0)=-70'; data=SimulateModel(eqns,'time_limits',[0 200]); figure; plot(data.time,data.pop1_v))



Larger models can easily build on existing model objects (e.g., "mechanisms").

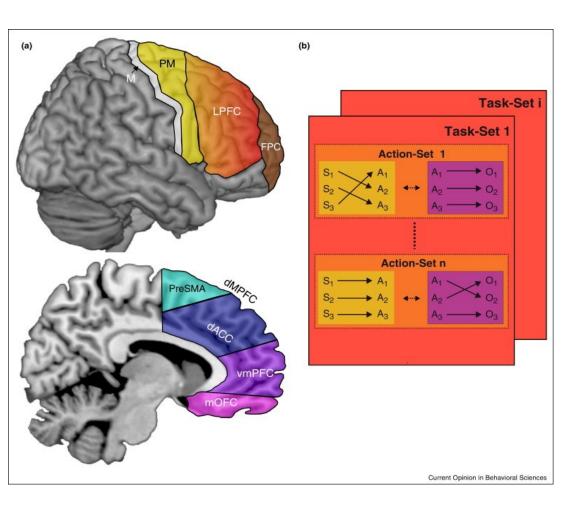
DynaSim – Graphical Interface for Modeling and Simulation

www.GitHub.com/DynaSim

SAVE MODEL **DynaSim Model Designer Equation View** Simulation View populations intrinsic mechanism lists size master equations ▲ - 8 dv/dt=Iapp+@current+noise*randn(1,N pop); ina, ik + 50 E_ina_m 20 - 2 dv/dt=Iapp+@current+noise*randn(1,N_pop); ina, ik + E ina h E_ik_n E I iGABAa -20 -40 Build detailed models from existing -60 mechanisms is as easy as writing -90 lists. connections mechanisms parameters **Mechanism Editor** l ina m 20 ▲ % FAST SODIUM CURRENT (Durstewitz 2000) E.ina l ina h 0 E.ik l ik n LE_iAMPA_s I.ina INa(v,m,h) = -gNa.*m.^3.*h.*(v-50) -20 I.ik qNa=120 -40 I->E.iGABAa dm/dt = aM(v).*(1-m)-bM(v).*mE->I.iAMPA -60 dh/dt = aH(v).*(1-h)-bH(v).*hh(0) = .1L-90 $m(\Theta) = .1$ aM(v) = (2.5-.1*(v+65))./(exp(2.5-.1*(v+65))-1) bM(v) = 4*exp(-(v+65)/18)aH(v) = .07*exp(-(v+65)/20) bH(v) = 1./(exp(3-.1*(v+65))+1)Adjust parameters during @current+=INa interactive simulation functions of one variable aM(v) = (2.5-.1∛▲ bM(v) = 4*exp(-(25 Inspect and tune auxiliary functions aH(v) = .07*exp(20 aM bH(v) = 1./(exp)ЬМ 15 aH 1 ЬΗ Display QuickSim Start .01 20e3 [-100.100] trace dt ntime -60 -40-20 60 80 -100-8040 10 y autoscale 200 ⊖ image NEW SWEEP View history + Version

View full model equations and dynamics during interactive model building

Rule-Based Cognitive Control



- <u>Cognitive control</u>: process of manipulating task-relevant info while ignoring distractors.
- DLPFC exerts cognitive control by biasing info flows in service of goals (pathway selection). It codes context-dependent "rules" (i.e., abstract sets of IF/THEN statements that direct input-output mappings), indicating what is relevant and how to manipulate it.
- <u>ACC monitors</u> diverse signals (e.g., errors, conflicts, reward) to perform a cost/benefit analysis for regulating cognitive control (e.g., <u>updating</u> rules).

I will focus on how network rhythms may contribute to rule-based cognitive control through their effects on dynamics in ACC and DLPFC (monitoring, updating, biasing).

Domenech, Koechlin. Current opinion in behavioral sciences 2015.

Prefrontal Rhythms: Experimental Motivation

M2

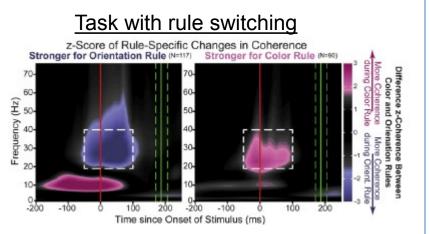
fmi

ACd

PrL

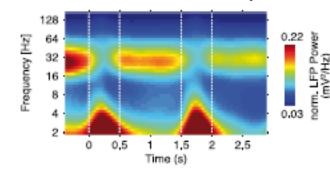
M1

PFC Rhythms in Cognitive Tasks



Active rule-selective ensembles are coherent with a beta2 oscillation

Buschman, Denovellis, Diogo, Bullock, Miller. Neuron 2012.



Two-item short term memory task

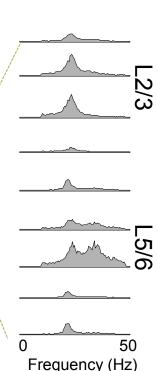
32Hz network rhythm during delay

Siegel, Warden, Miller, PNAS 2009

PFC Wants to Oscillate (in vitro)

IL DP 1 Carbachol/Kainate Anterior cingulate Prelimbic cortex Infralimbic cortex 100 μV • • 100 msec

LeBeau (unpublished data)



Network freq. depends on:

- cortical region
- cortical layer
- agonist/antagonist

Results: From Dynamics to Function

Outline

1. Background

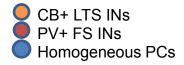
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<u>Question</u>: How do rhythms contribute to rule-based pathway selection?

(ACC) (LIP, STG) Rule Stimulus LPFC (WM) Cognitive Contro 1.1.1.1 R.

(conceptual model)

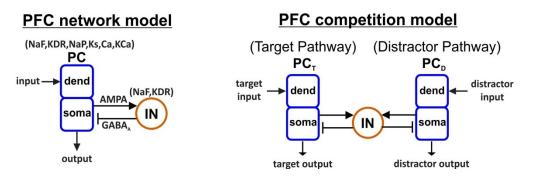
(Goal-directed biases)



(computational model)

We will see:

- There is beta resonance in deep layers, even though FS cells can support gamma resonance.
- Pathways with resonant inputs can be selected over stronger pathways with less resonant inputs.

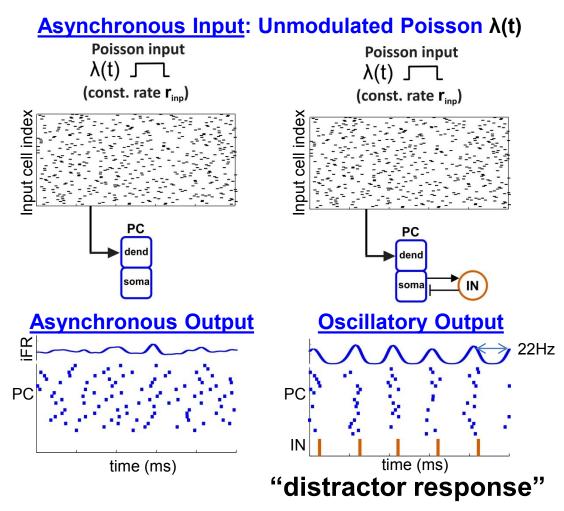


Biophysical PFC L5 cell model:

$$C_m \frac{dV_{PY}}{dt} = I_{ext}(t) - I_{Na} - I_K - I_{NaP} - I_{Ca} - I_{KCa} - I_M - I_h - I_{leak}$$

Durstewitz, Daniel, and Jeremy K. Seamans. Neural Networks 15.4 (2002): 561-572

Feedback Inhibition Produces Natural Oscillation

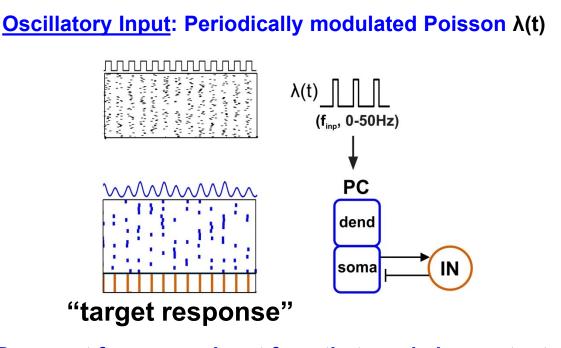


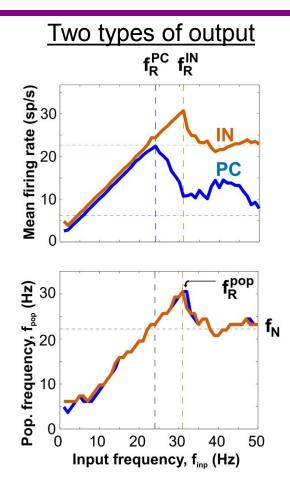
- Strong feedback inhibition turns asynchronous input into an oscillatory output at the level of the population.
 (not necessarily visible in single cells)
- <u>Population frequency</u> = the frequency of population oscillation.
- <u>Natural frequency</u> = population frequency in response to an asynchronous input.

PC/IN Network Response is:

- Inhibition-paced: pop frequency decreases with inhibition duration.
- Variable-freq oscillator: pop frequency increases with input strength.

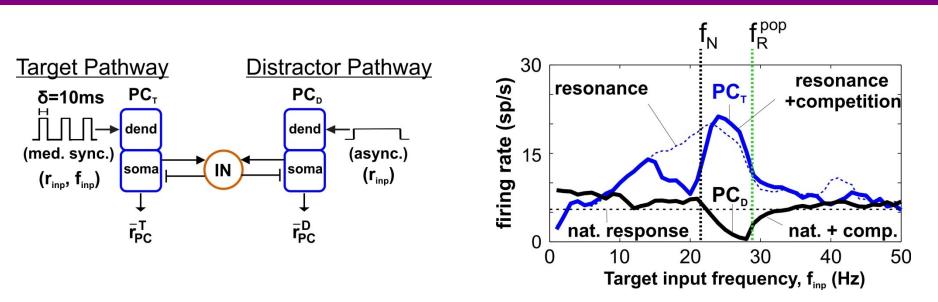
Oscillatory Input Produces Greater Output





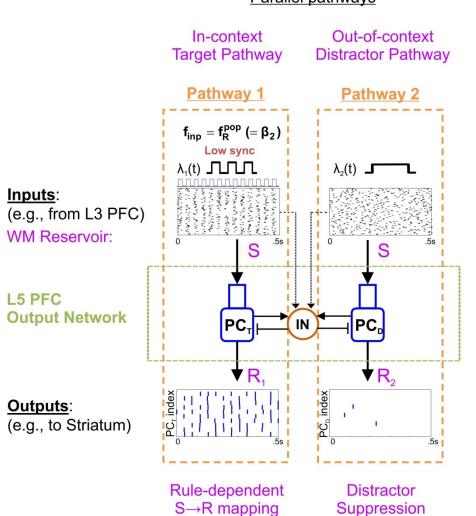
- **Resonant frequency: Input freq. that maximizes output.**
- IN cells exhibit higher FR resonant frequency
- Max. pop. frequency = FR resonant freq (IN)
- Despite cell differences, PC and IN pops exhibit the same rhythmicity
- Resonant frequencies increase with input strength
- Max pop. frequency always exceeds natural frequency (i.e., it is always possible for the target to oscillate faster than distractor)

Biased Competition: Resonant Target Suppresses Asynchronous Distractors



- Resonant inputs gate response to competing asynchronous activity.
- Suppression occurs when <u>target pop. freq. > natural freq.</u> of distractor.
 - Per cycle, target PCs drive INs before distractor PCs reach thresh.
- Stronger async. distractors can be suppressed by more sync. targets.
- High sync. target can produce more spike output than 70% stronger async. distractor.
- Suppression can be amplified for winner-take-all selection by recurrent excitation within output pops (i.e., learning across trials).

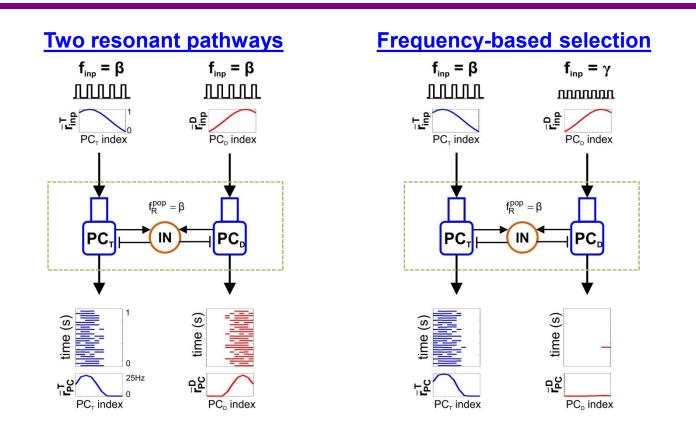
Cognitively-Relevant Example of Distrator Suppression (Gating) with Rhythm-Mediated Biased Competition



Parallel pathways

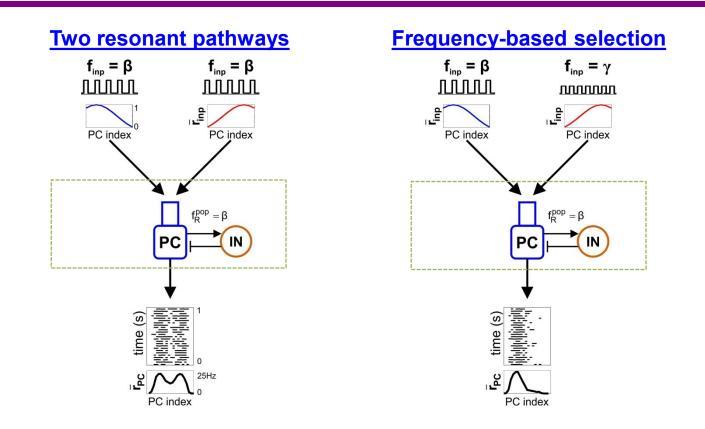
- Pathway selection depends on matching input frequency to output resonant frequency.
- LPFC L2/3 rule-related betarhythmic assembly successfully drives L5 target.
- LPFC L2/3 asynchronous
 "memory" is retained in
 superficial layers without driving
 L5 target (i.e., without being
 transmitted to downstream
 targets).

Resonant Bias Can Gate Rate-Coded Signals Among Parallel Pathways



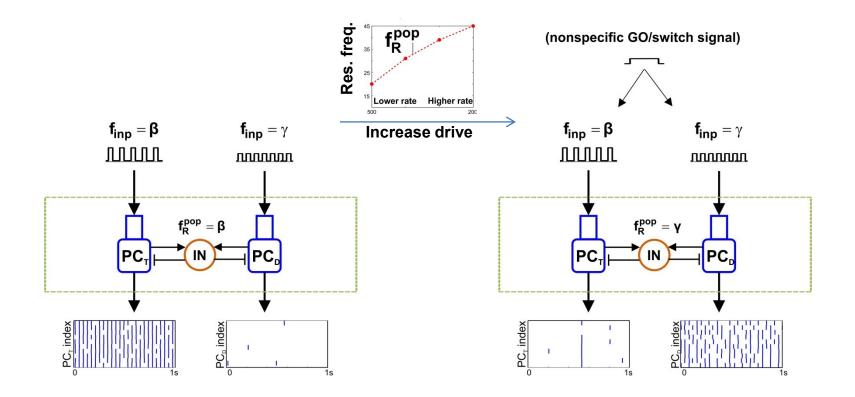
- Input pattern of firing rates is reflected across the output populations.
- A resonant input phase locks with INs and suppresses response to less resonant signal.
- A more coherent input can suppress response to less coherent signal.

Resonant Bias Can Gate Rate-Coded Signals Among Convergent Pathways



- Firing rate pattern of multiple inputs can be reflected across a single output population.
- A resonant input phase locks with INs and blocks response to less resonant signal.

Nonspecific Input Selects Beta vs. Gamma by Setting Target Resonant Frequency



- "GO" \rightarrow <u>output layer</u>: dominant pathway switches w/ target res. freq.
- "GO" → input layer (variable-freq. oscillators): source freq. increases w/ target res. freq., and the same pathway remains dominant.

Summary / Discussion (so far): Connection to Cognitive Processes

DLPFC:

- Can control which <u>input-output mappings</u> are engaged by controlling participation in a <u>resonant oscillation</u>.
- Separation of representations in superficial and deep layers allows <u>memory</u> in superficial layers to be <u>distinct from output</u> (beta)
- Can <u>flexibly tune resonant frequency</u> via input rate and <u>tune</u> <u>degree of response</u> through synchrony of the input.

Implication: Non-specific GO signal can lead to specific outcome

Outline

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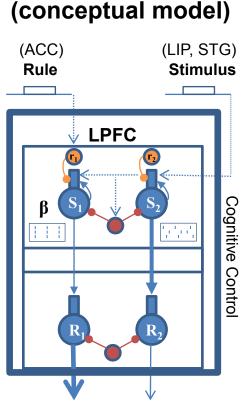
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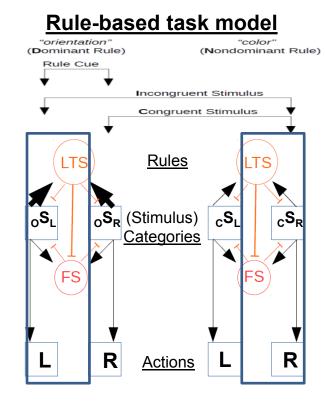
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LPFC Cognitive Rhythms: Rule Selection

<u>Question</u>: What controls rule-specific beta-rhythmicity? H: Context (rule) is represented by activation of subset of CB+ LTS interneurons. Leads to resonant beta frequency activity in superficial layers.





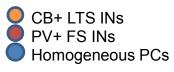
Key differences between IN types

- Inhibition strength: LTS > FS (LTS → more coherent PCs)
- Inhibition duration: LTS > FS (LTS → beta rhythmic PCs)

(beta res. in deep layers)

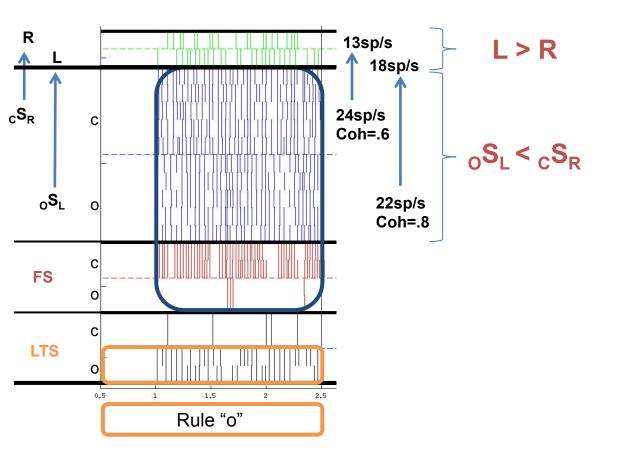
(Incongruent stimulus: maps to different responses in different rules)

(Goal-directed biases)



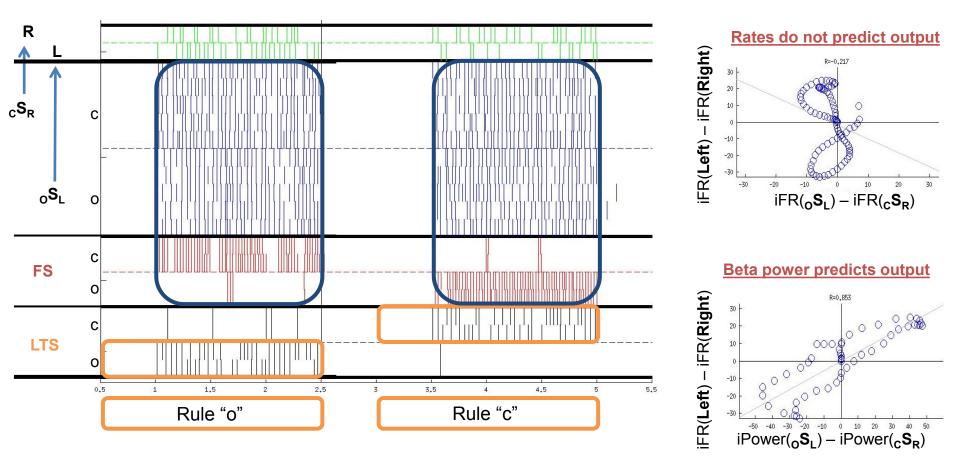
<u>Consider</u>: two trials with the same incongruent stimulus ($_{O}S_{L}$, $_{C}S_{R}$) and different contexts/rules ("o" vs "c").

CB+ LTS Activity Selects Beta-Rhythmic Assembly, and thus Response Mapping Via Biased Competition



Driving LTS cells selects mapping inhibited by them (via resonant beta-rhythmic bias).

CB+ LTS Activity Selects Beta-Rhythmic Assembly, and thus Response Mapping Via Biased Competition



- The only change from one rule to the next is which LTS cells were driven.
- The output is predicted by LTS-dependent beta power, not input firing rates.

Conclusions for DLPFC

 Context-sensitive LTS inhibition induces betarhythmicity in coupled assemblies (collectively specifying a "rule"). Could be triggered by transient input from ACC.

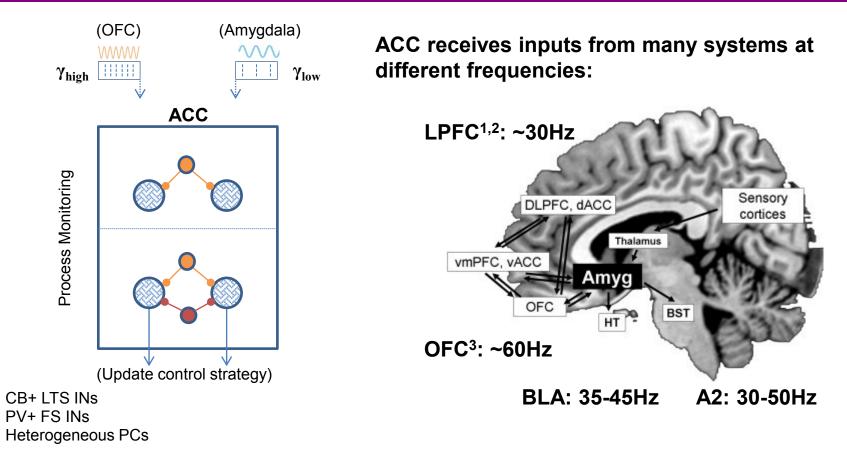
• Resonance-mediated bias for rule-dependent action: the beta-rhythmic assembly produces greater spiking in its target relative to a higher spike rate non-rhythmic assembly.

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ACC Heterogeneity for Process Monitoring

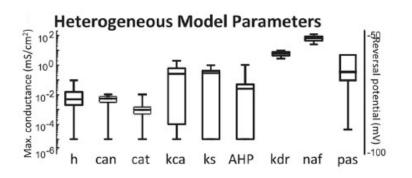


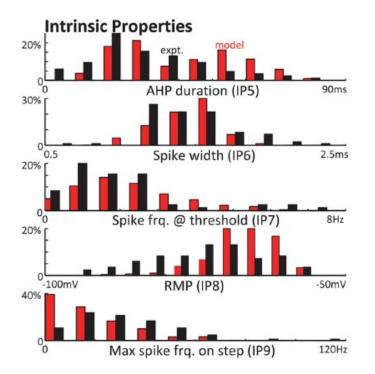
- ACC monitors diverse signals (e.g., errors, conflicts, reward, uncertainty) for cost/benefit analysis to allocate resources for cognitive control.
- ACC outputs to PFC are implicated in updating rules for decision making.

Question: How does ACC combine inputs at different frequencies?

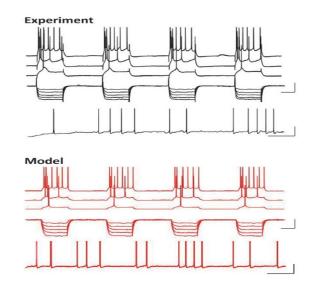
[1] Siegel, Warden, Miller. PNAS 2008. [2] Buschman, Denovellis, Diogo, Bullock, Miller. Neuron 2012. [3] Pennartz, van Wingerden, Vinck. Annals of NY Acad of Sciences 2011.

Heterogeneous Biophysical Models Reproduce the Range of Experimental Intrinsic Properties



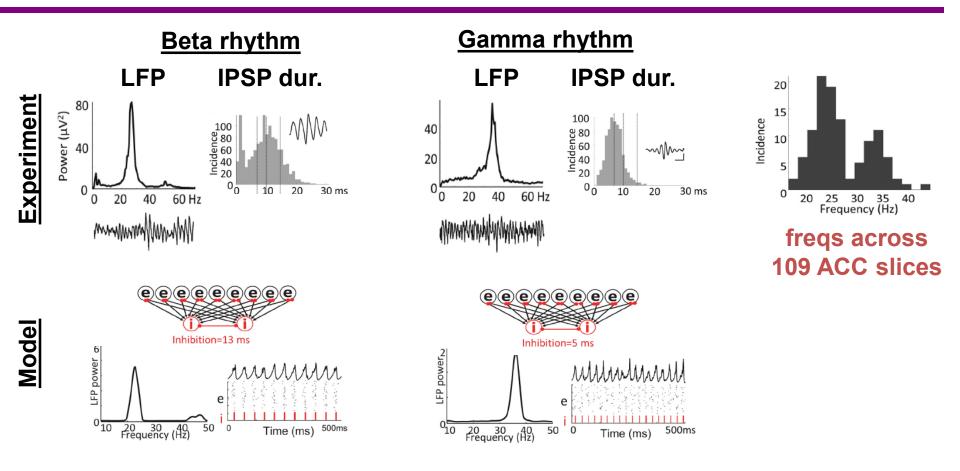


- Recorded 61 (isolated) cells in ACC
- Modeled heterogeneity:
 - Simulated experimental protocol
 - Varied 9 parameters
 - Constrained 5 intrinsic properties
 - Tested >100,000 cell models
 - Found 2,810 viable models

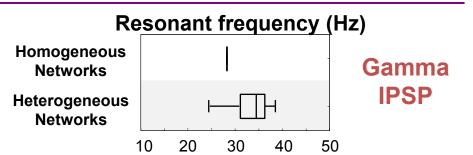


ACC E-cells have intrinsic properties that are <u>heterogeneous</u> across the population.

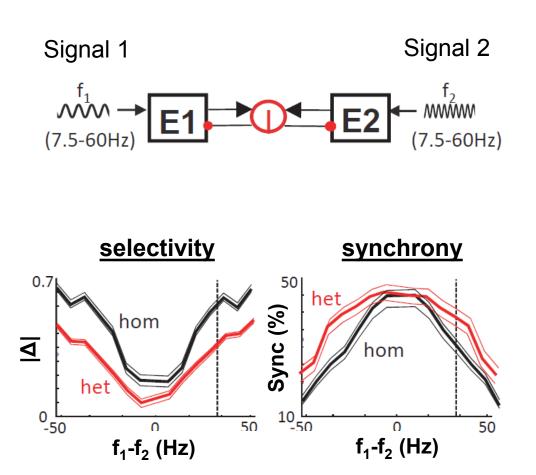
IPSPs Suggest Dual Inhibitory Inputs in ACC Cells During Gamma/Beta Network Oscillations



Heterogeneity expands the range of input frequencies that produce a (firing rate) resonant response.



Heterogeneity of Target Decreases Selectivity and Increases Synchrony



 Δ = (fractional difference in firing rate) Sync = (percent of 10ms bins with spiking in both assemblies)

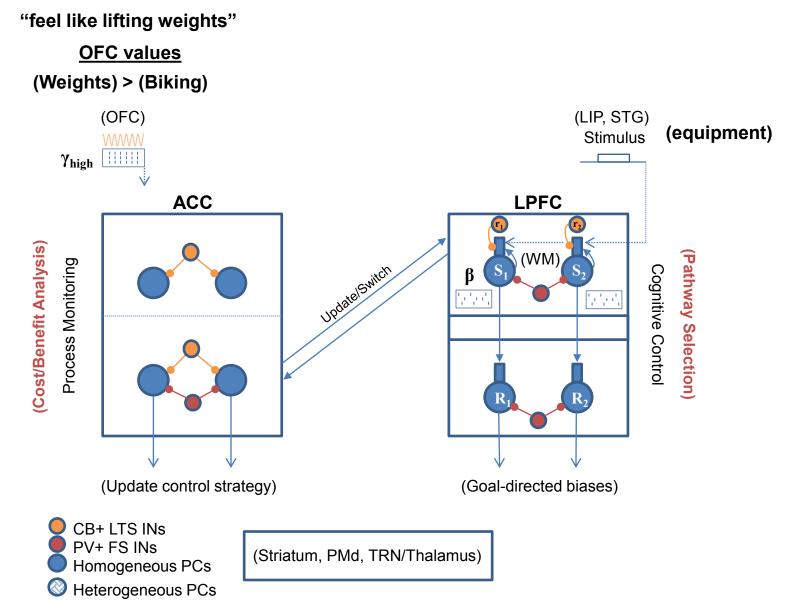
- Networks with competing assemblies are <u>less selective</u> for input frequencies when Ecell assemblies are heterogeneous. Outputs are <u>more synchronous.</u>
- Heterogeneity has little effect when frequency differences are small.
- Similar result for assemblies driven by rhythmic vs. asynchronous activity.
- ACC heterogeneity may facilitate combinatorial evaluation for rule updating/task switching.

ACC:

 Heterogeneity in target reduces competition and allows combination of signals associated with monitoring outcomes for updating cognitive control strategies (and possibly choice of rule)

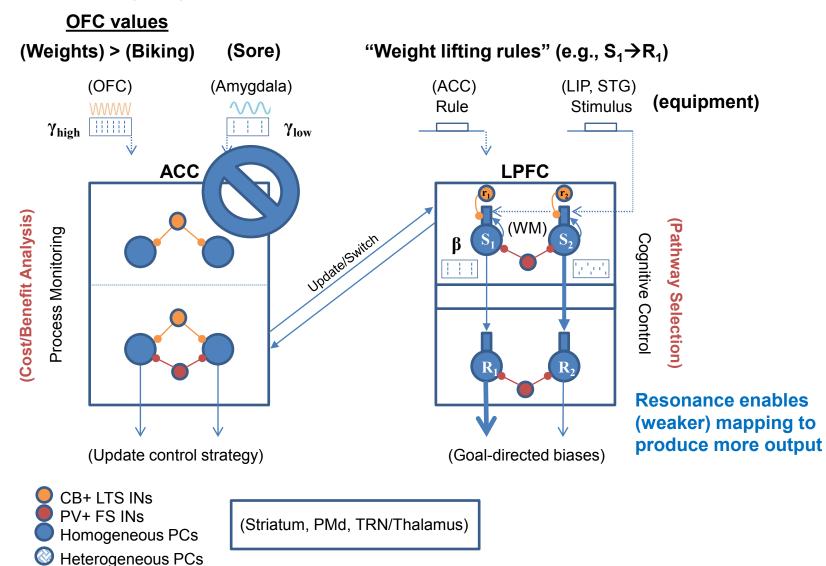
 May provide signals that (directly or indirectly) update the "context" by activating selected CB+ cells in superficial DLPFC





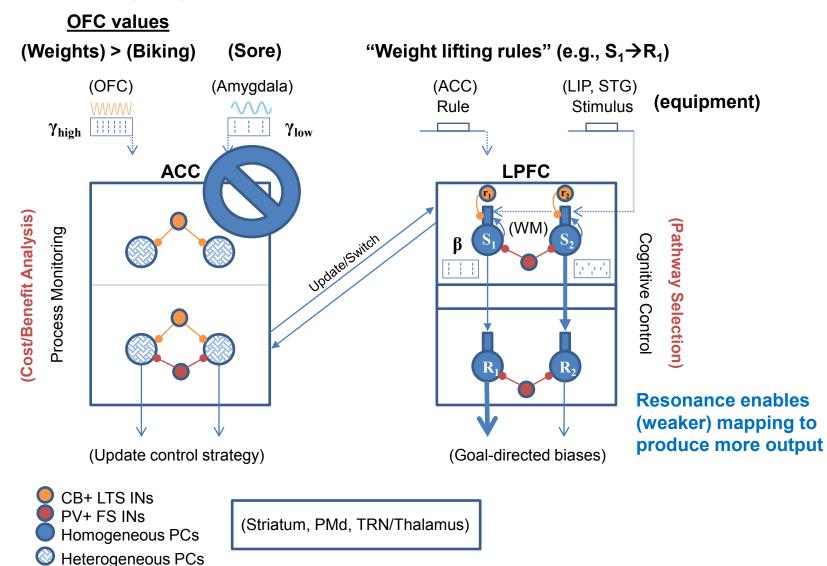
Example situation: choosing between lifting weights and biking at gym.

"feel like lifting weights"



Example situation: choosing between lifting weights and biking at gym.

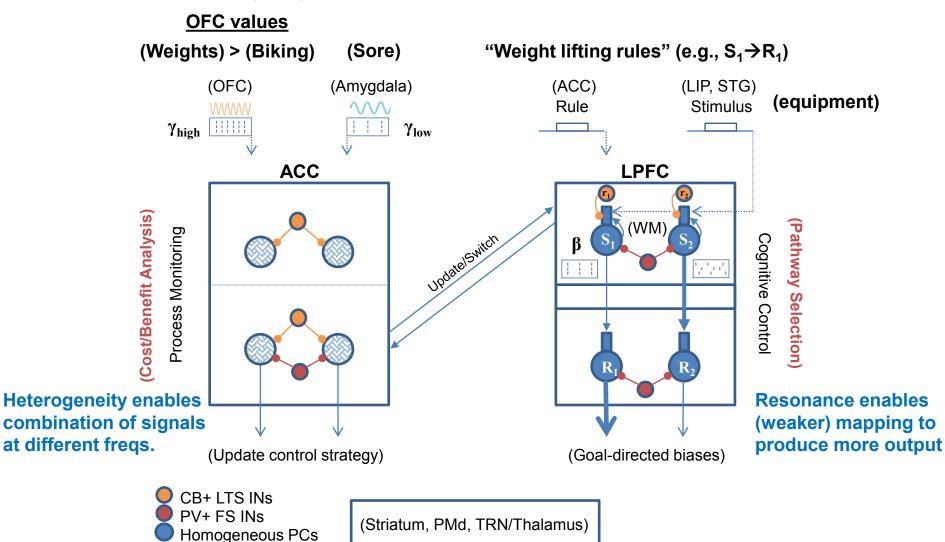
"feel like lifting weights"



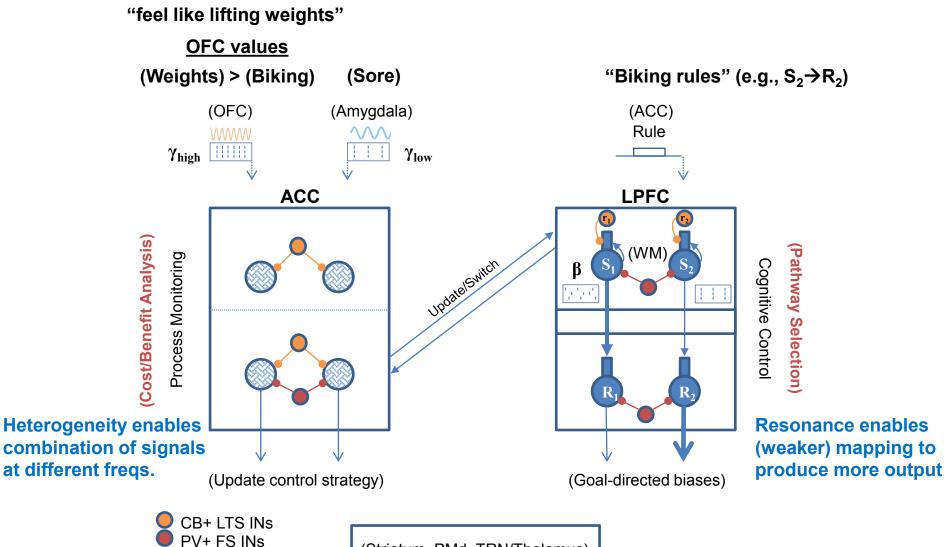
Example situation: choosing between lifting weights and biking at gym.

"feel like lifting weights"

Heterogeneous PCs



Example situation: choosing between lifting weights and biking at gym.



Homogeneous PCs (S Heterogeneous PCs

(Striatum, PMd, TRN/Thalamus)

- Rhythms are important in coordination (e.g., establishing functional connectivity)
- Coordination is important in cognitive control
 - LPFC: gating and routing according to rule (choice of resonant pathway)
- Cell heterogeneity decreases selectivity
 - ACC: integration of signals, updating the active rule
- Tuning heterogeneity can switch a network between selective and combinatorial processing modes

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- NaK