Impact of Single-Neuron Dynamics on Transfer of Correlations from Common Input

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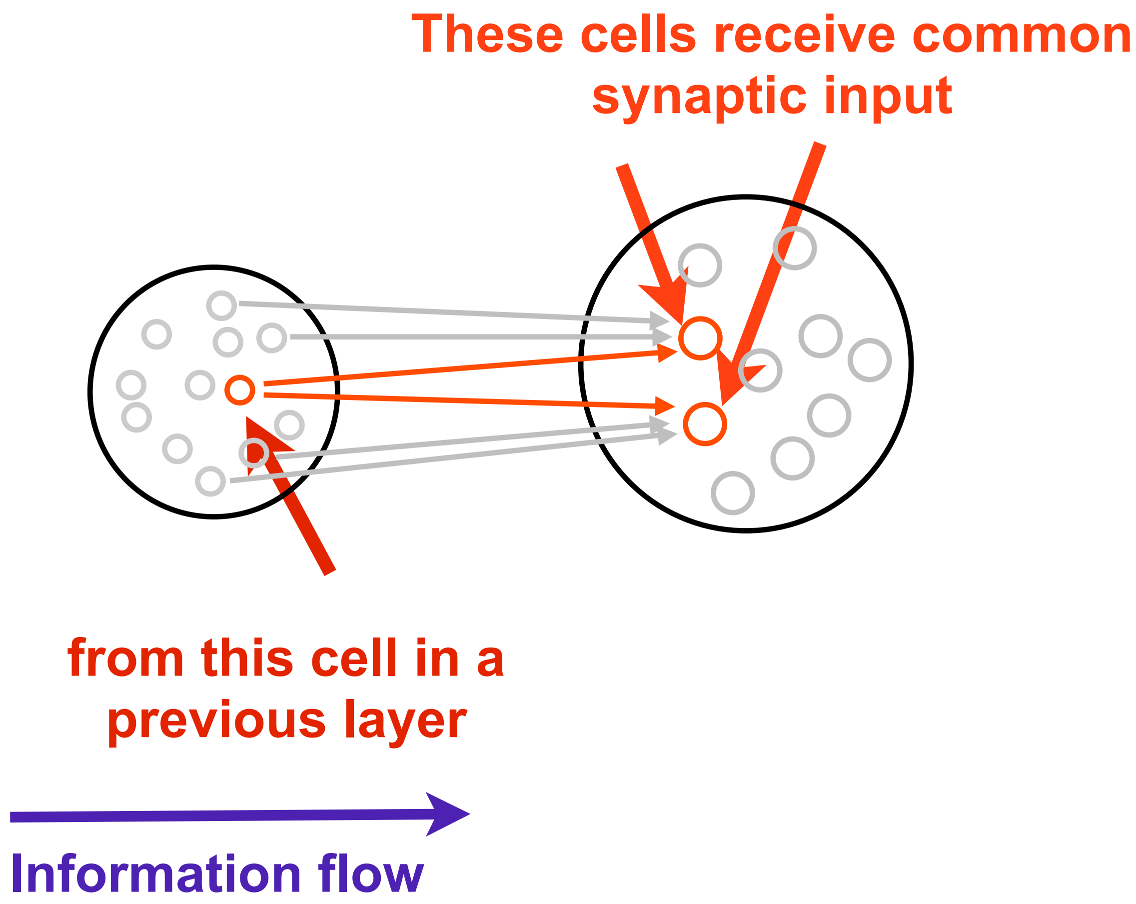
CNS Workshop on *Stochastic Neural Dynamics*
July 22, 2015

Common input from population coding creates correlations



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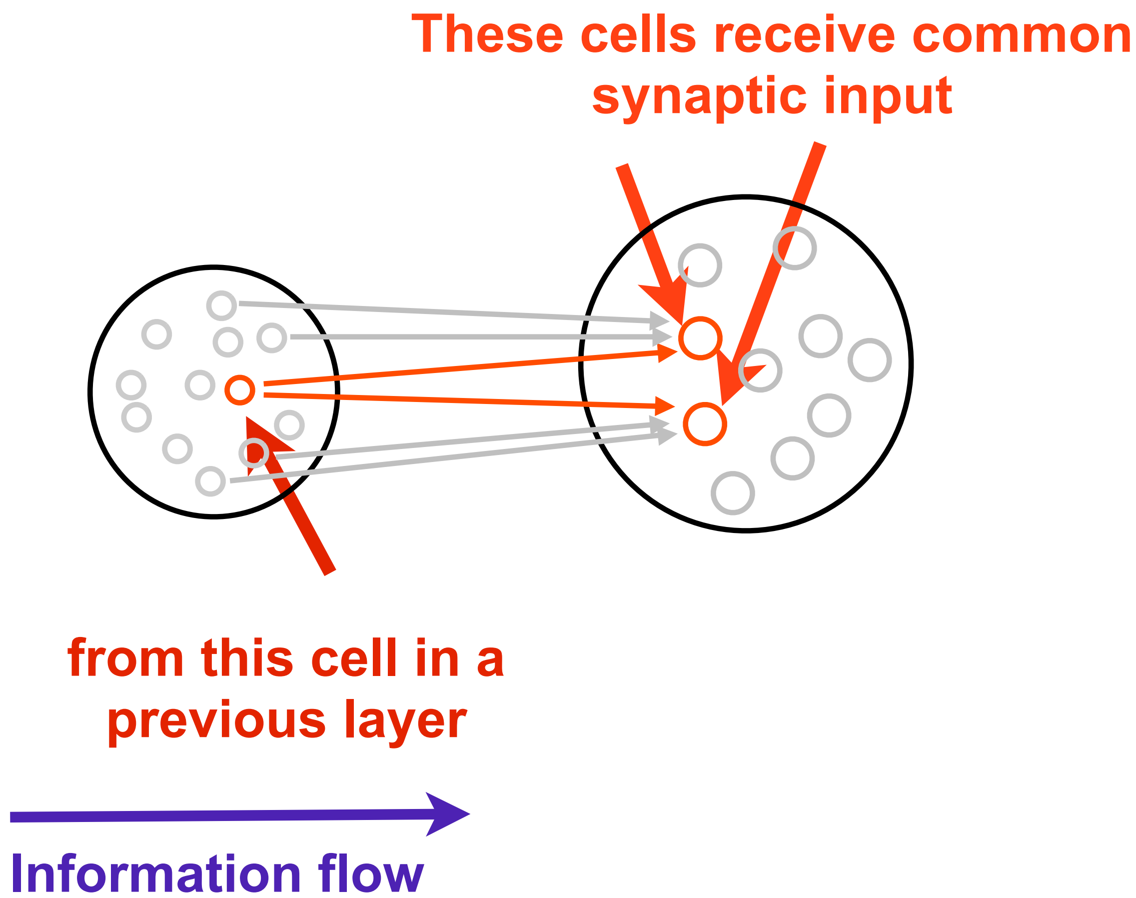

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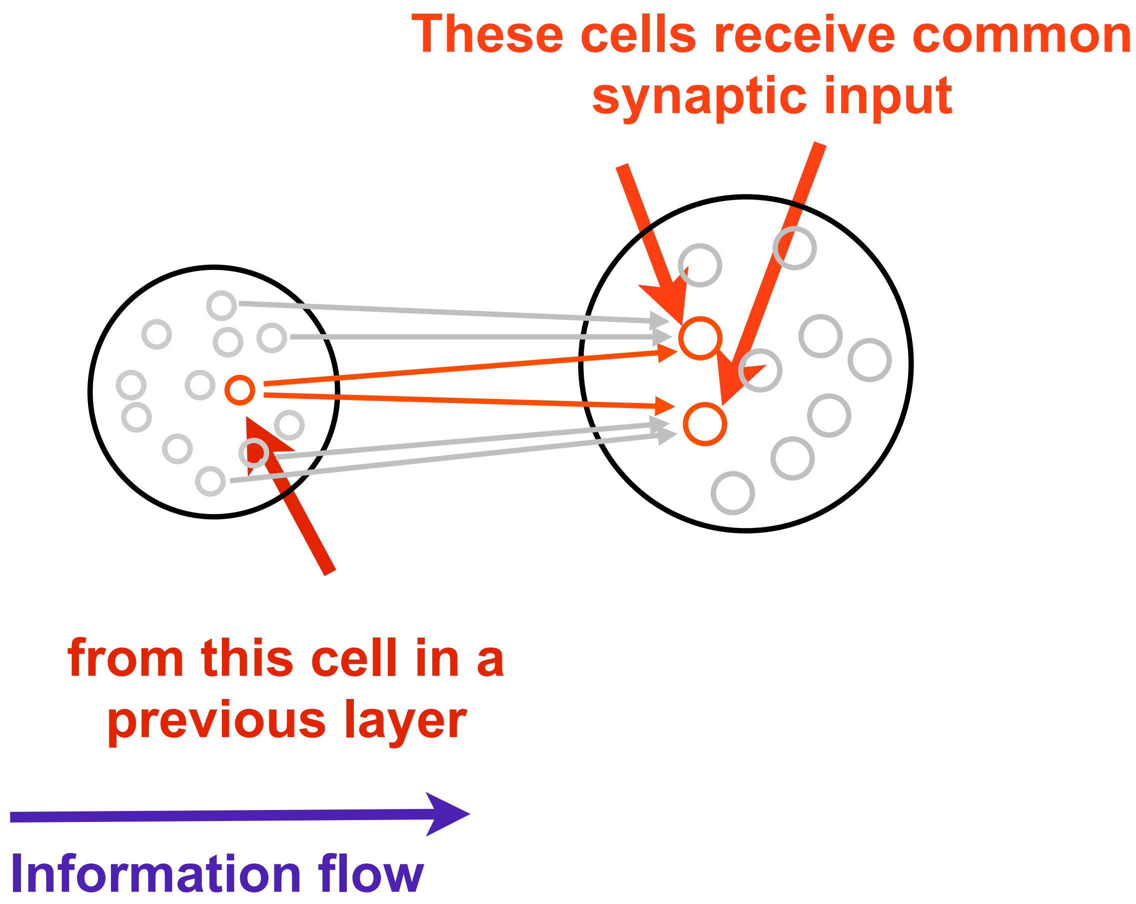

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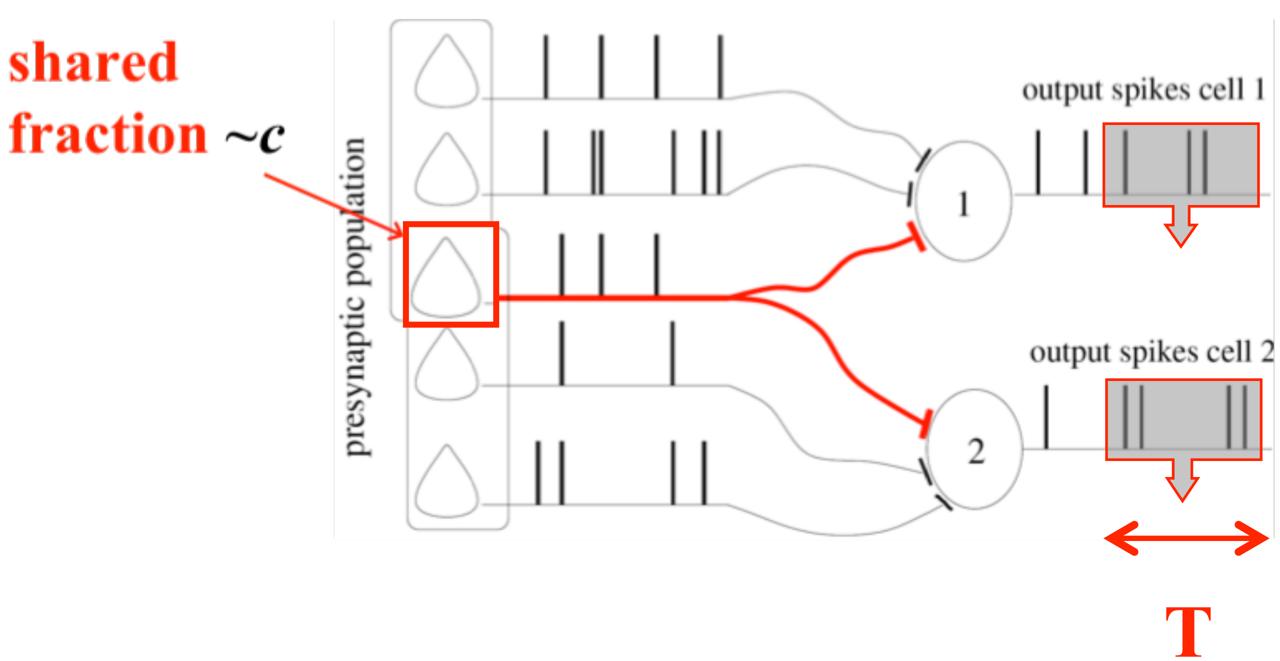
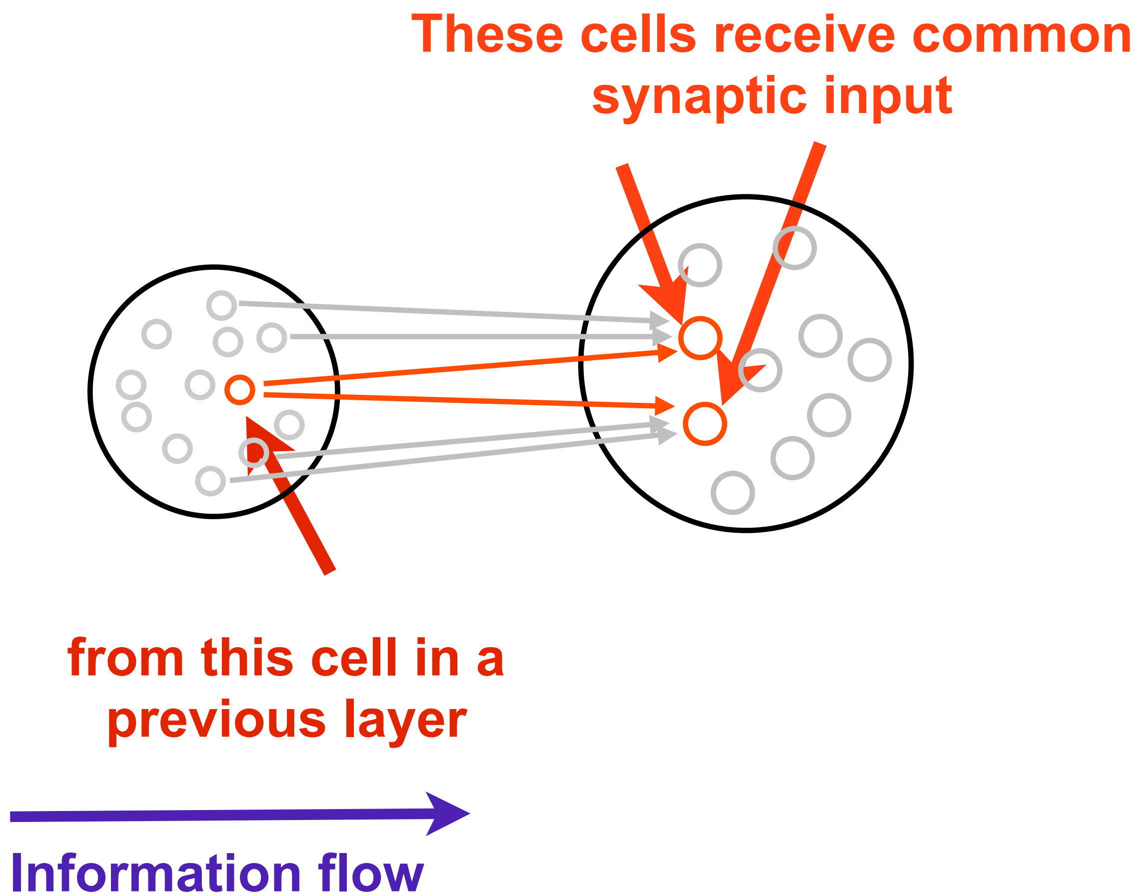


$$n_1 = 3$$

$$n_2 = 4$$

Common input from population coding creates correlations



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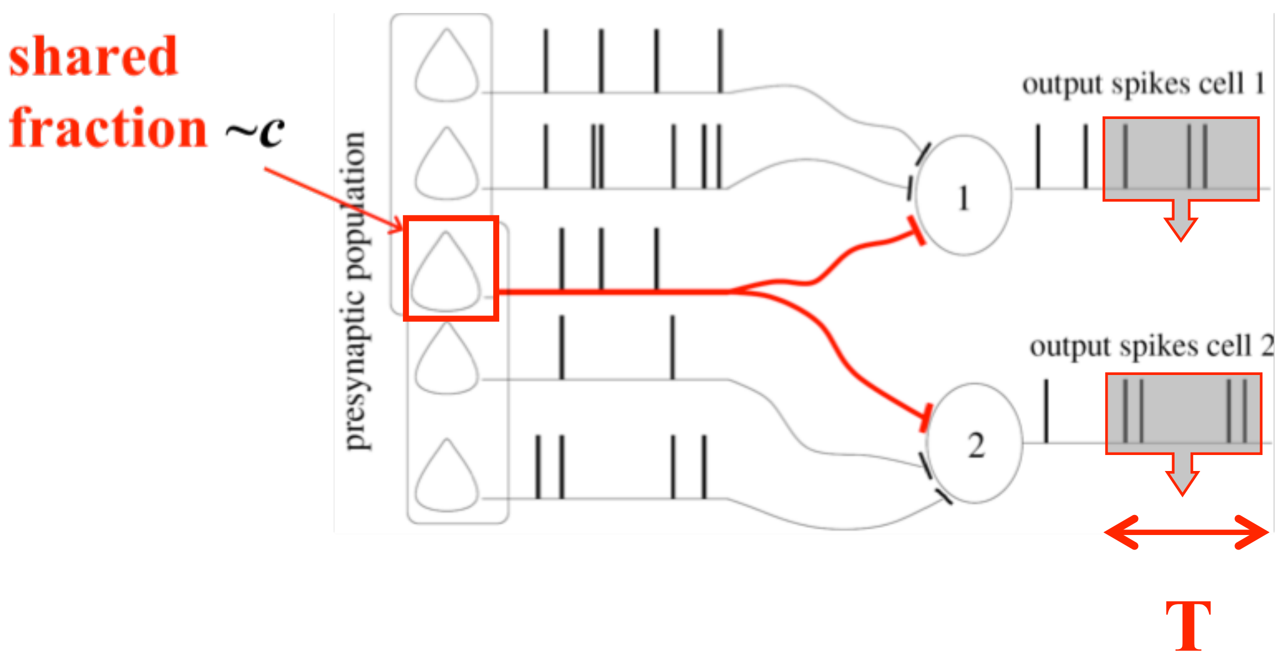

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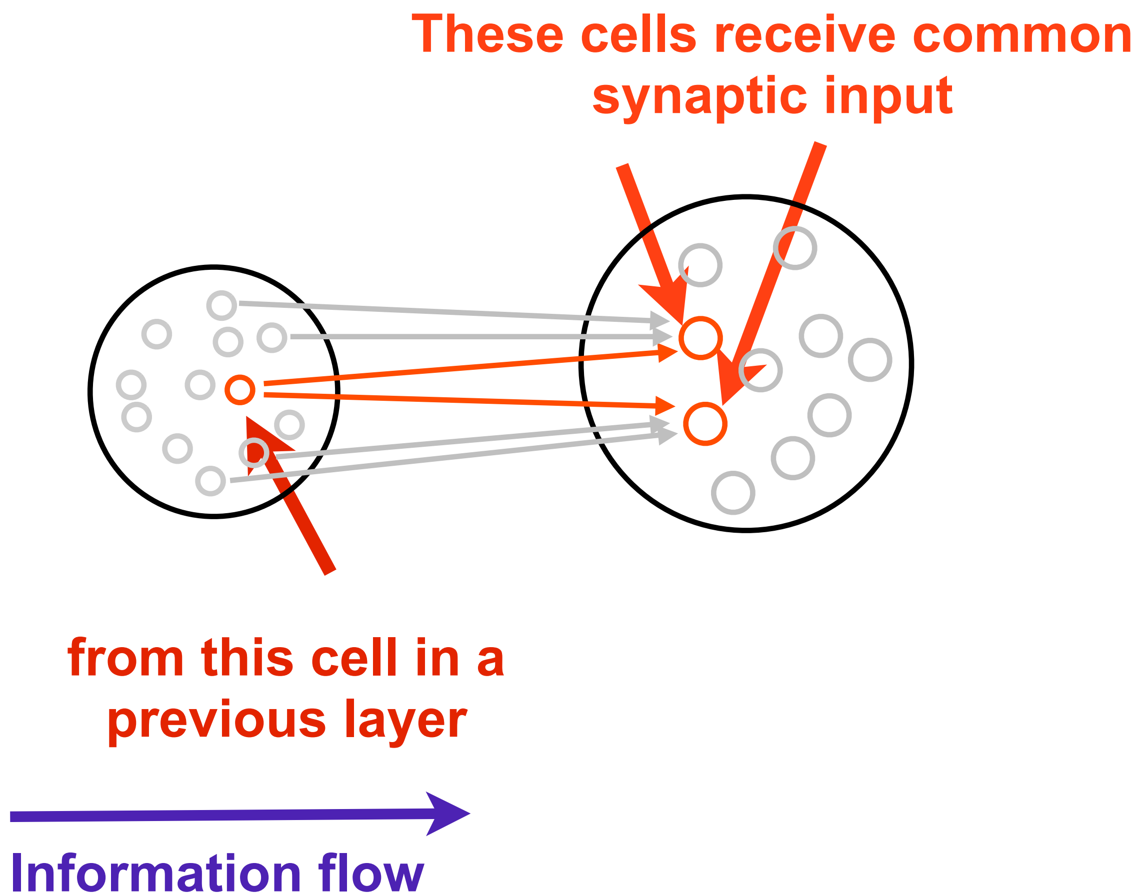

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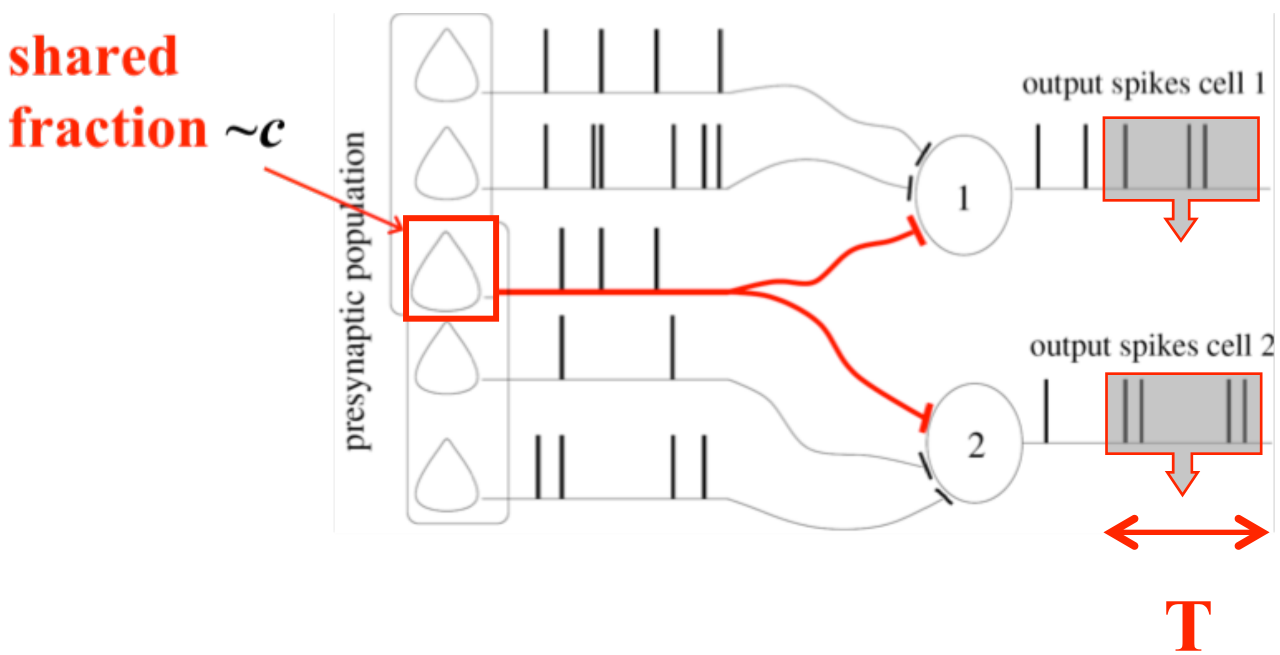

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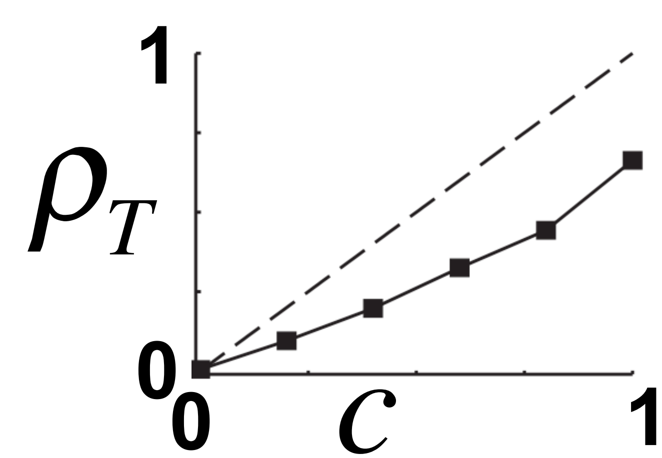
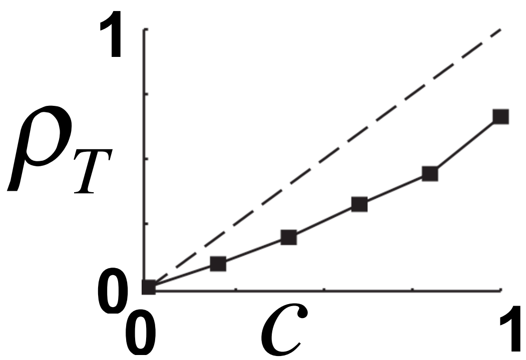


How does this relationship depend on single cell dynamics?



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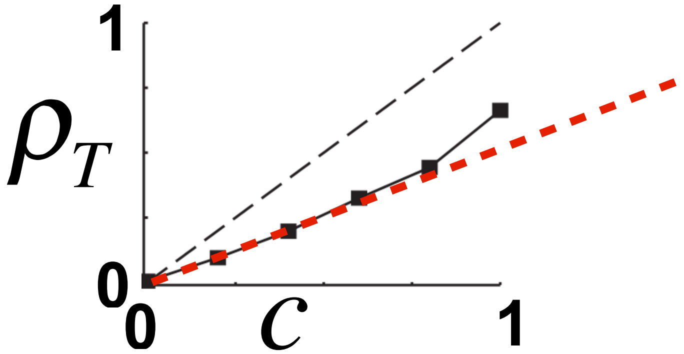
How does this relationship depend on single cell dynamics?

Linear response theory: for small noise, linear in c (cf. Lindner et al. 2005)



$$\rho_T \equiv \frac{Cov(n_1, n_2)}{\sqrt{Var(n_1)}\sqrt{Var(n_2)}} \approx cS_T$$

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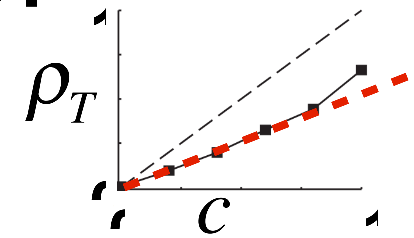

One way to characterize neurons: resting-to-spiking excitability

$$C\frac{dV}{dt} = I - g_K n^4 \left(V - E_K\right) - g_{Na} m^3 h\left(V - E_{Na}\right) - g_L\left(V - E_L\right) + I_{app}$$

$$\frac{dn}{dt} = \left(n_\infty(V) - n\right) / \tau_n(V)$$

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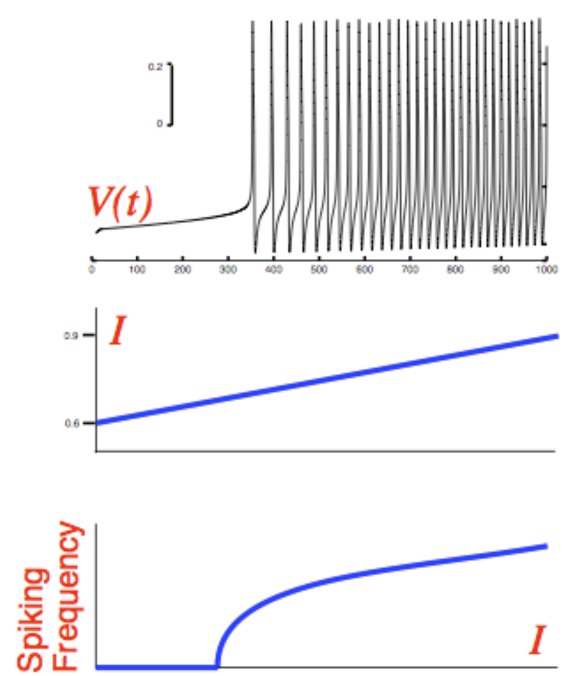

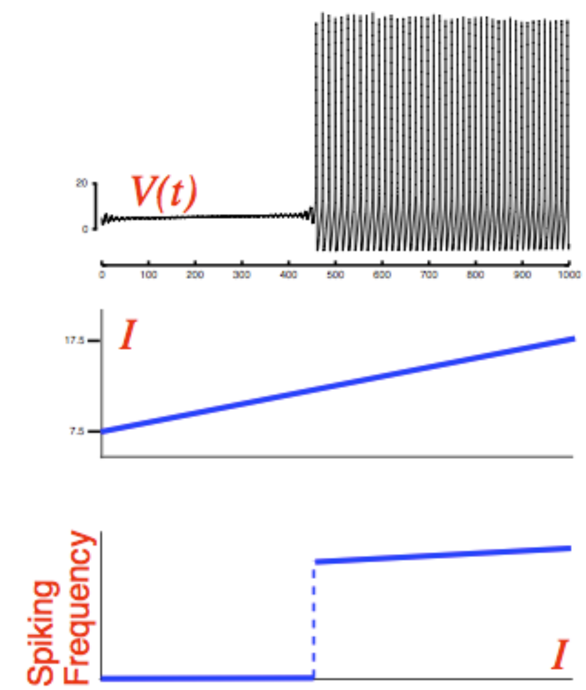

Figures: Guillaume Lajoie, UW

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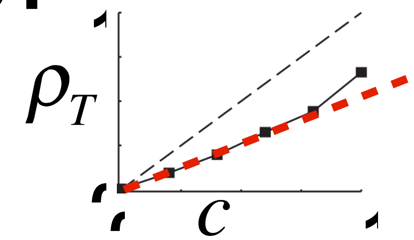

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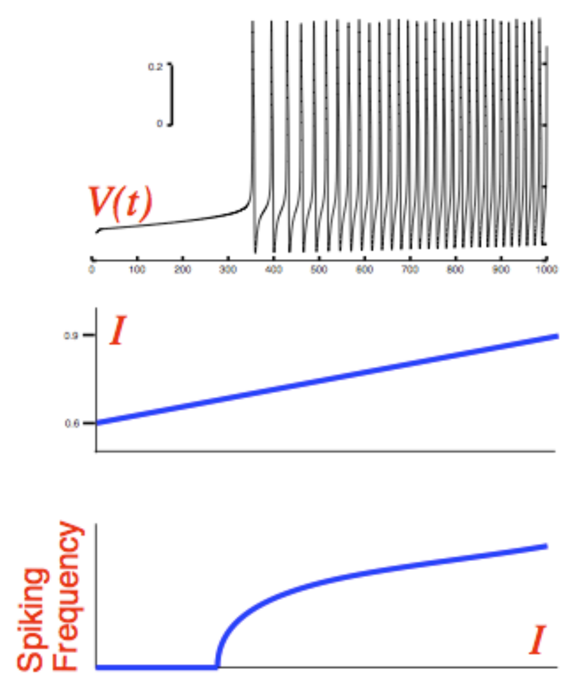
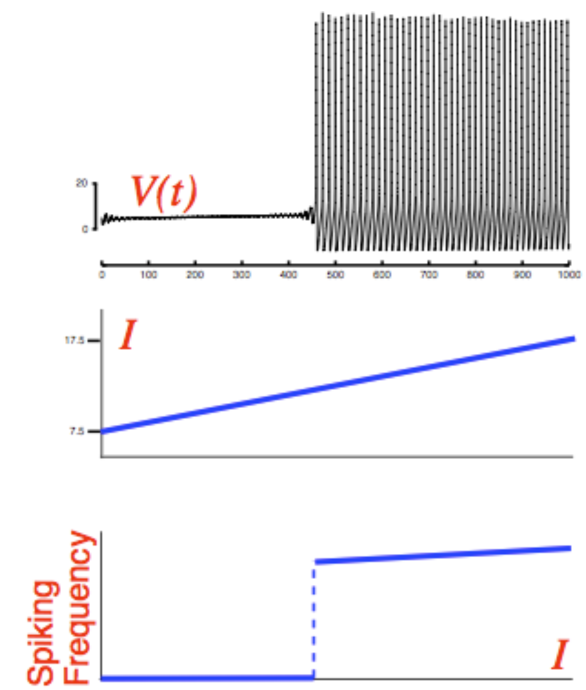


Type I excitability



Type II excitability

Figures: Guillaume Lajoie, UW

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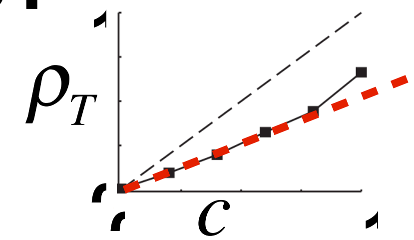

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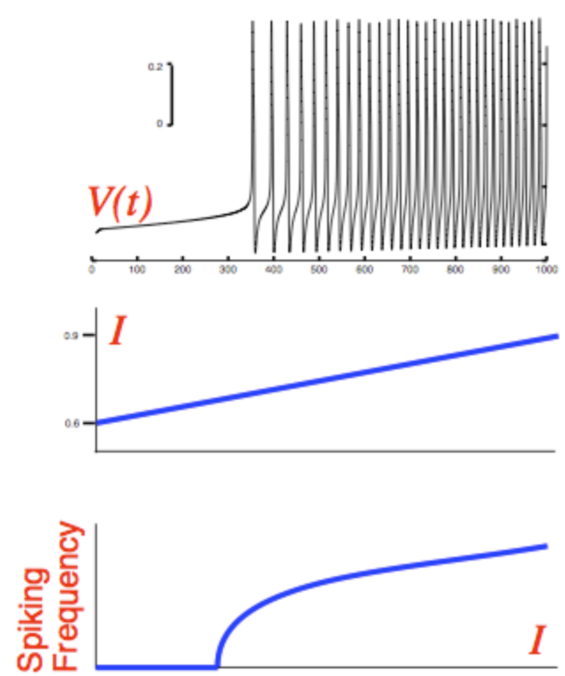

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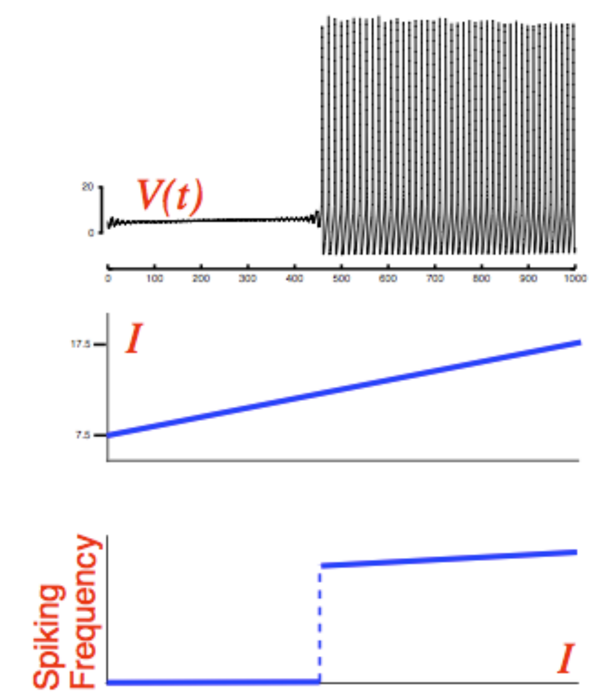

Type II excitability

Compare Type I vs. Type II dynamics:

- Stimulus selectivity and neurocomputational properties: integrator vs. resonator (Agüera y Arcas et al. 2003; Mato and Samengo 2008)
- Synchronization properties (Ermentrout 1996; Hansel et al. 1995; Wang and Buzsáki 1996)
- Type I/II transition can be effected by regulating slow potassium currents (Ermentrout et al. 2001), such as by neuromodulators (Steifel et al. 2008a, 2008b) or level of background activity (Prescott et al. 2008)

Figures: Guillaume Lajoie, UW

A neural model that shows both Type I and Type II excitability

Connor-Stevens model

(Connor and Stevens 1971, Connor et al. 1977, Rush and Rinzel 1994)

$$C\frac{dV}{dt} = I - g_K n^4 (V - E_K) - g_{Na} m^3 h (V - E_{Na}) - g_L (V - E_L)$$

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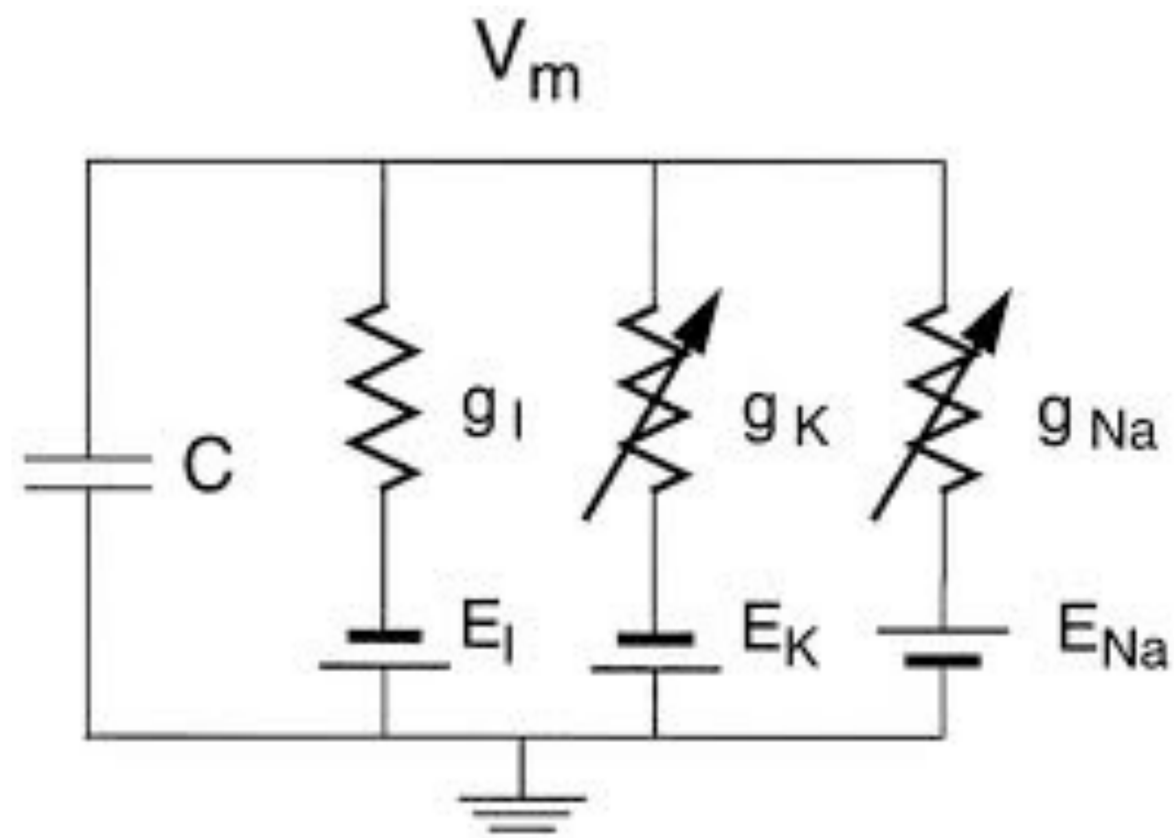

Hodgkin-Huxley

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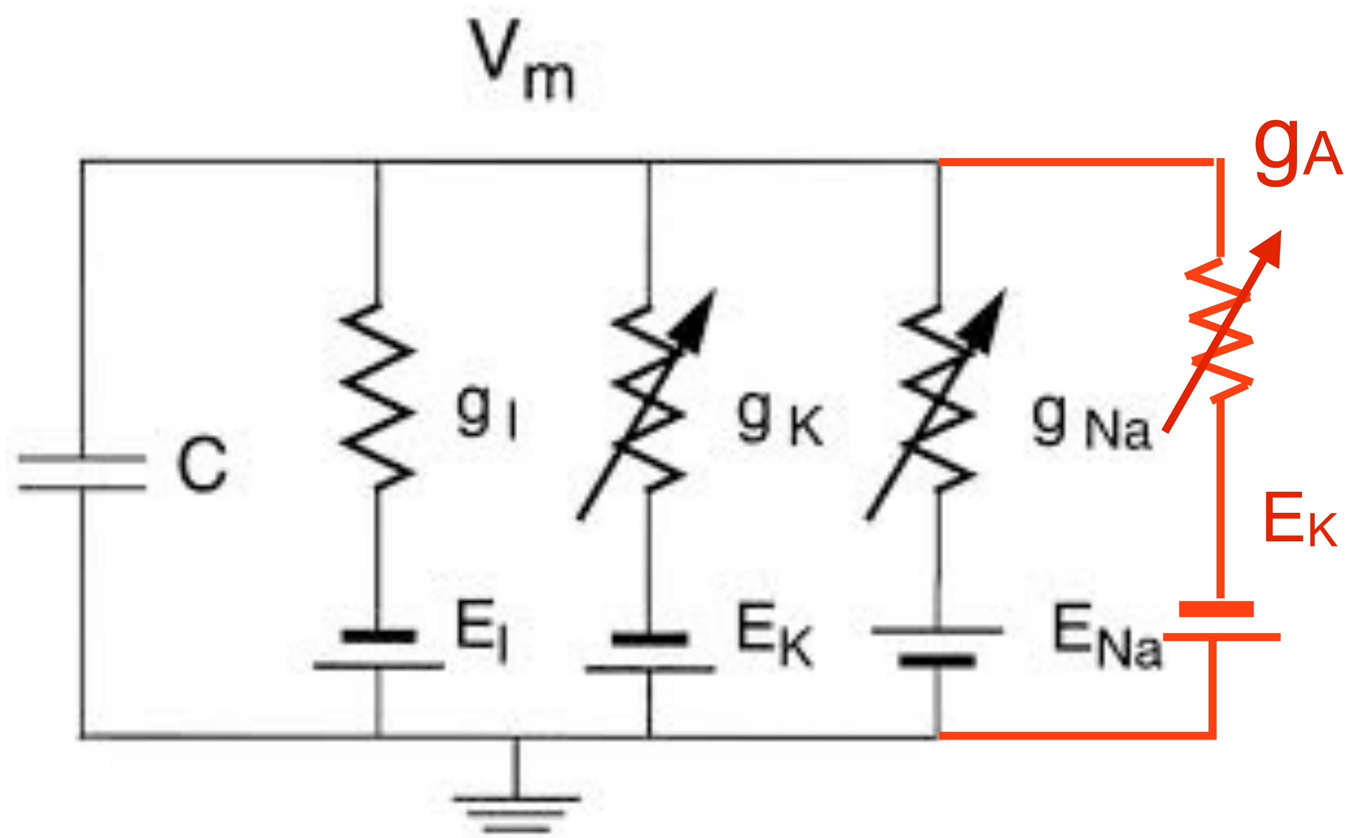

Hodgkin-Huxley + transient A-current

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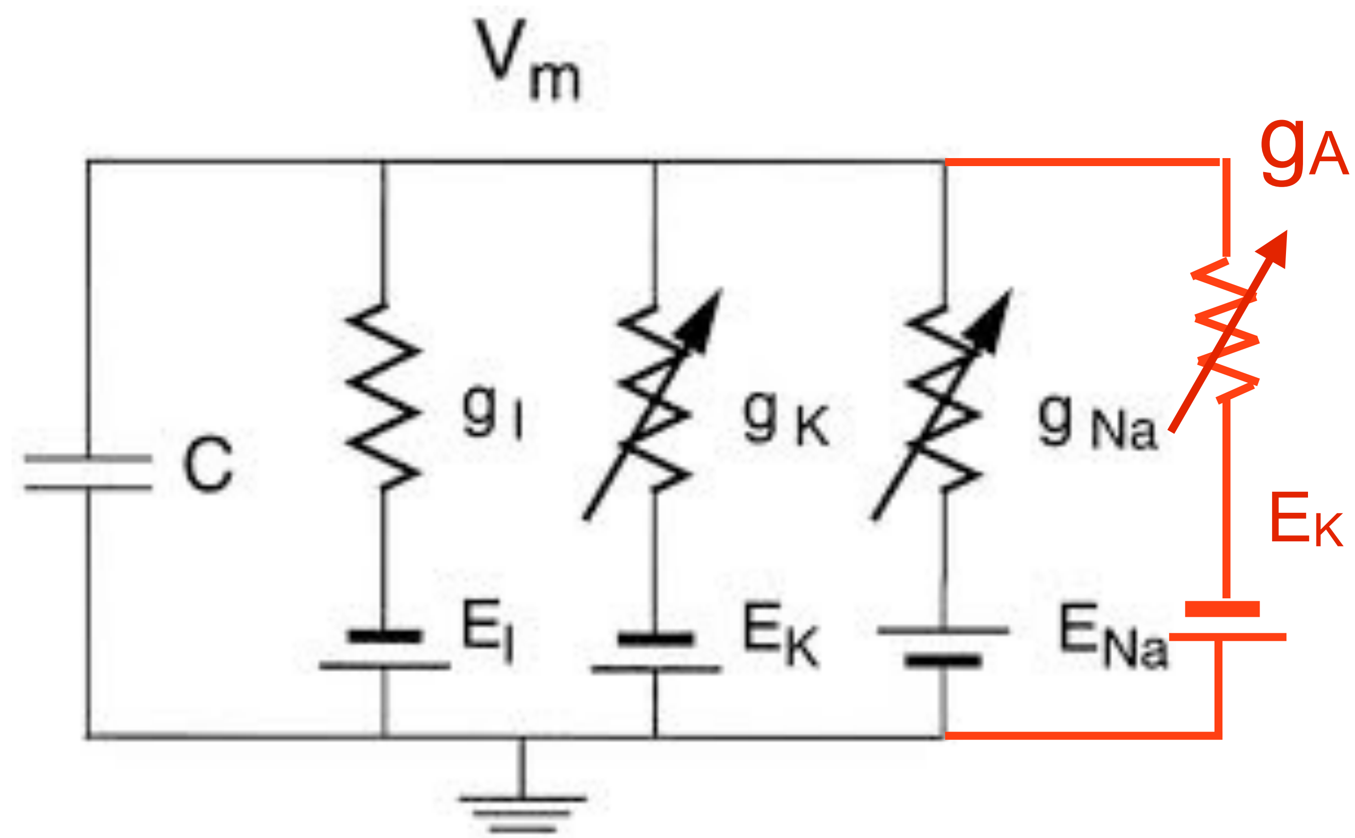
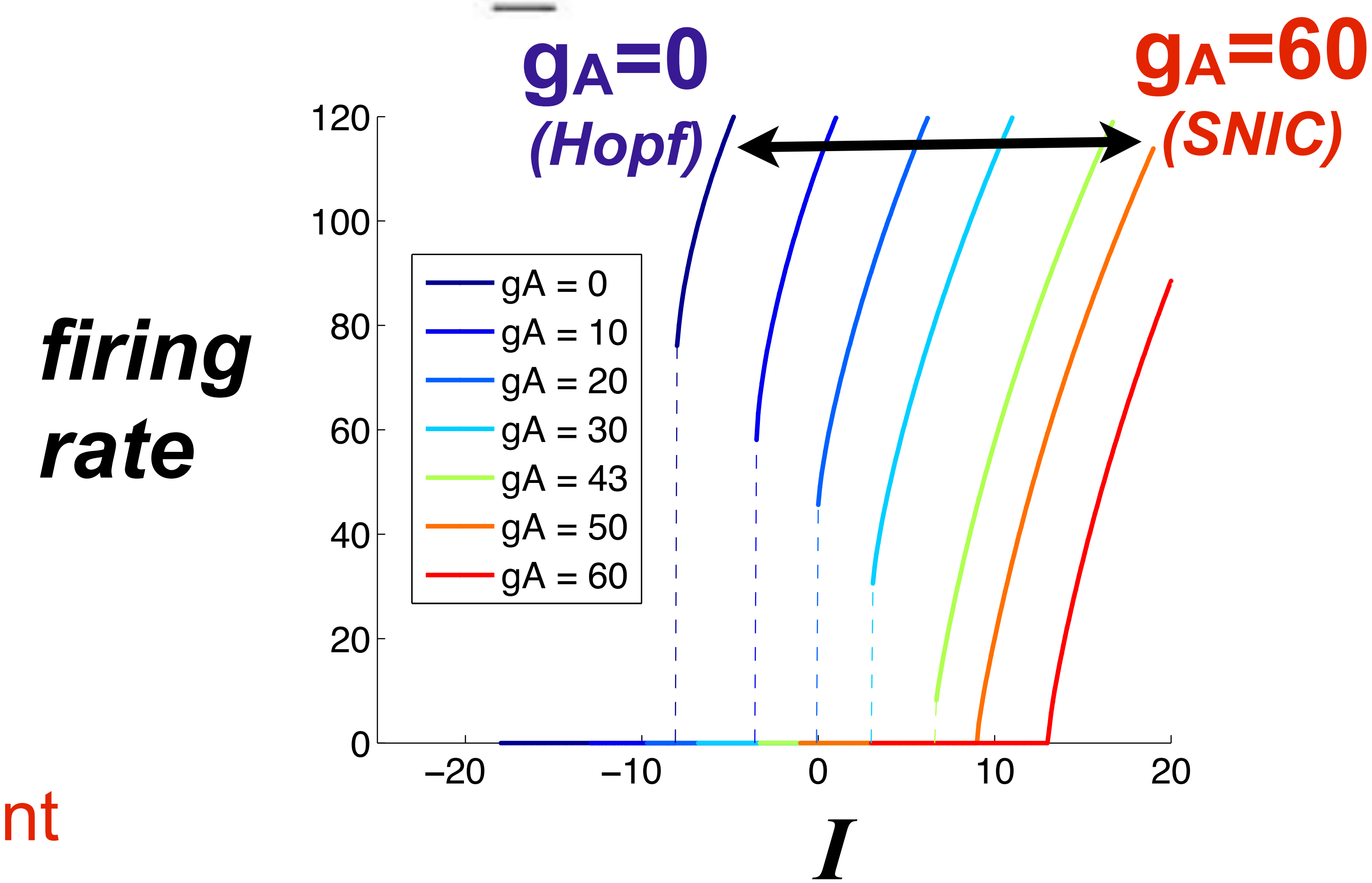
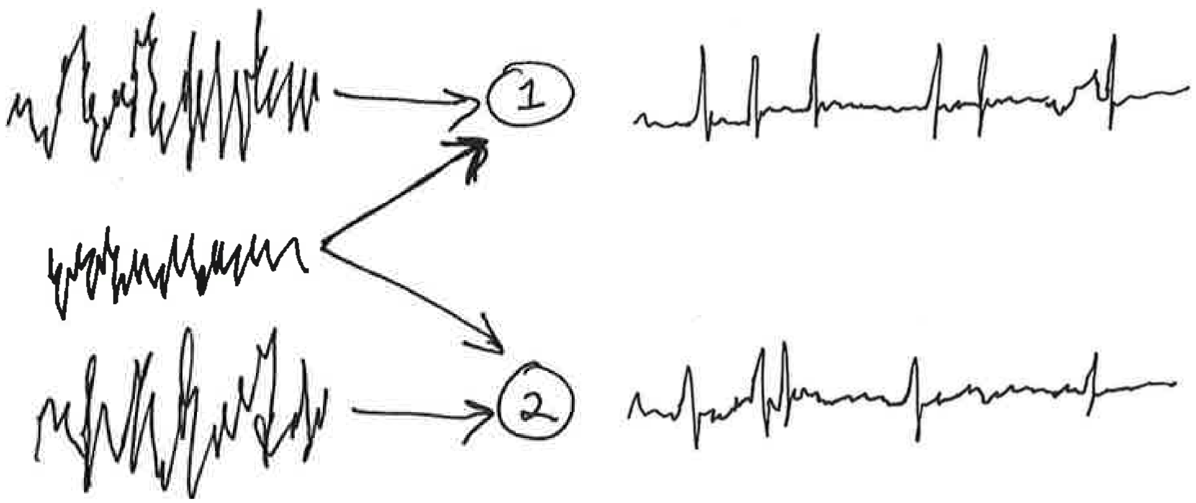
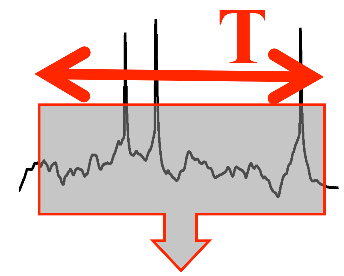




Correlation transfer efficiency reverses, based on time scale





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Barreiro et al., J Neurophysiology 2012

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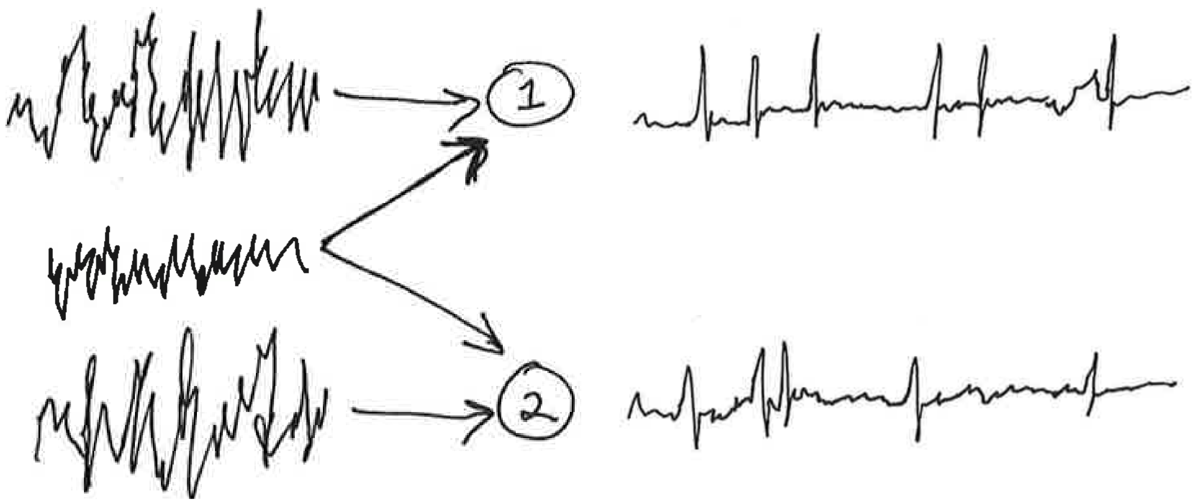

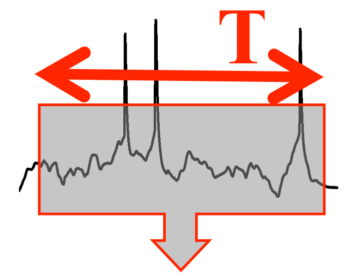

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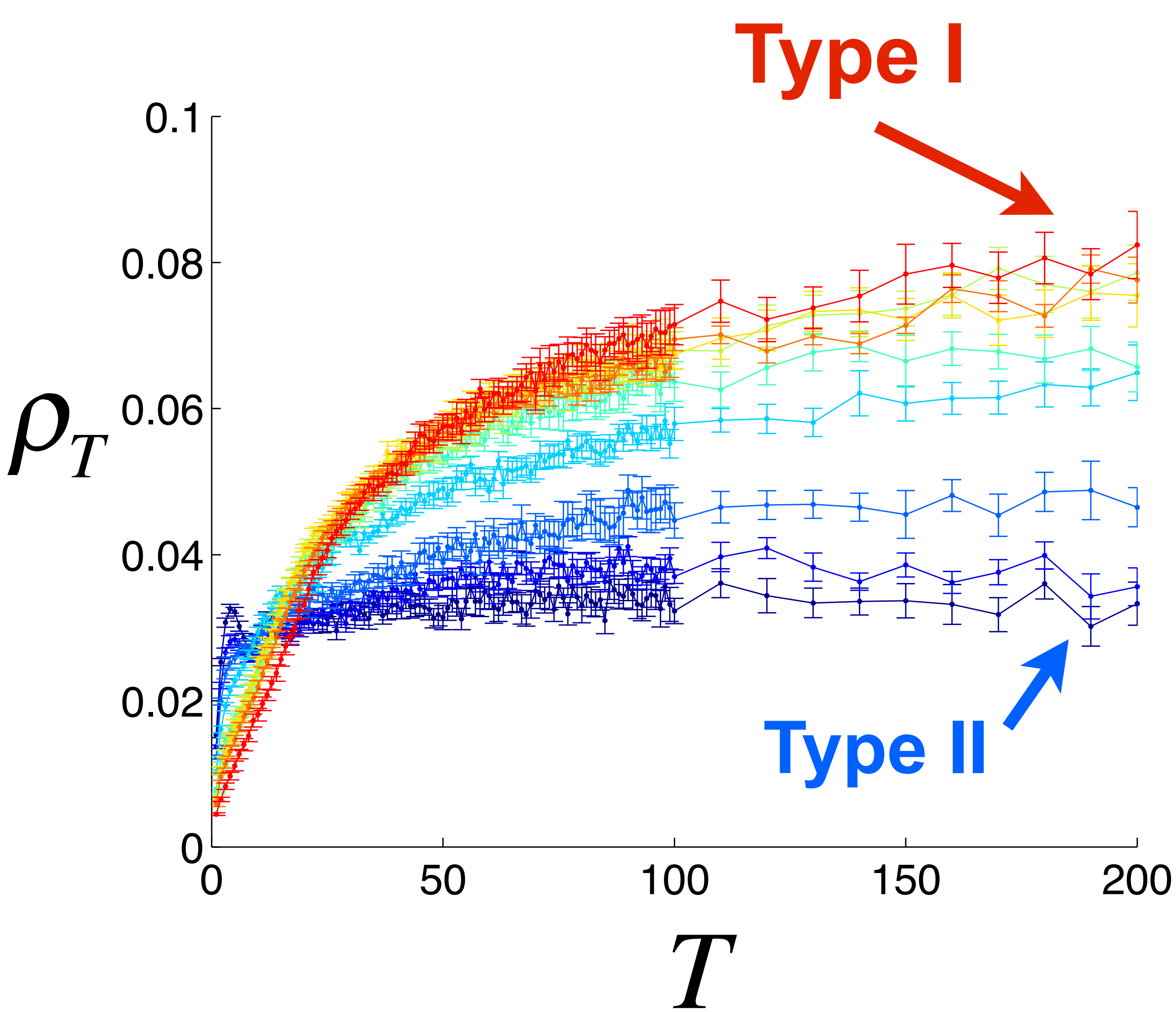

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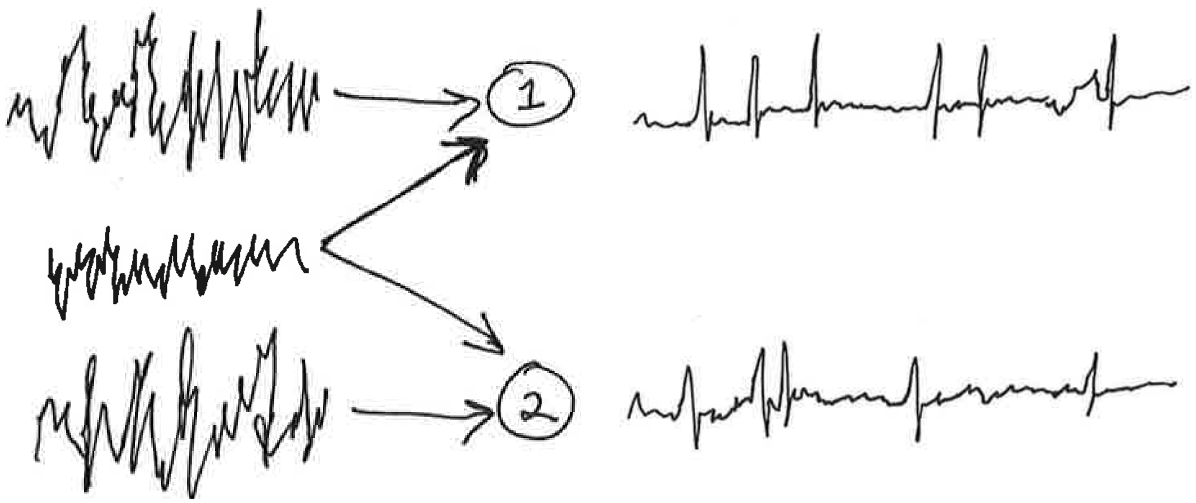

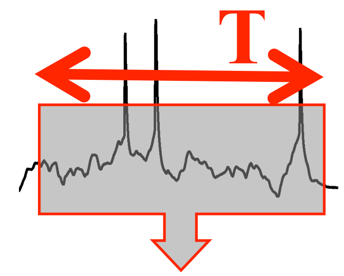

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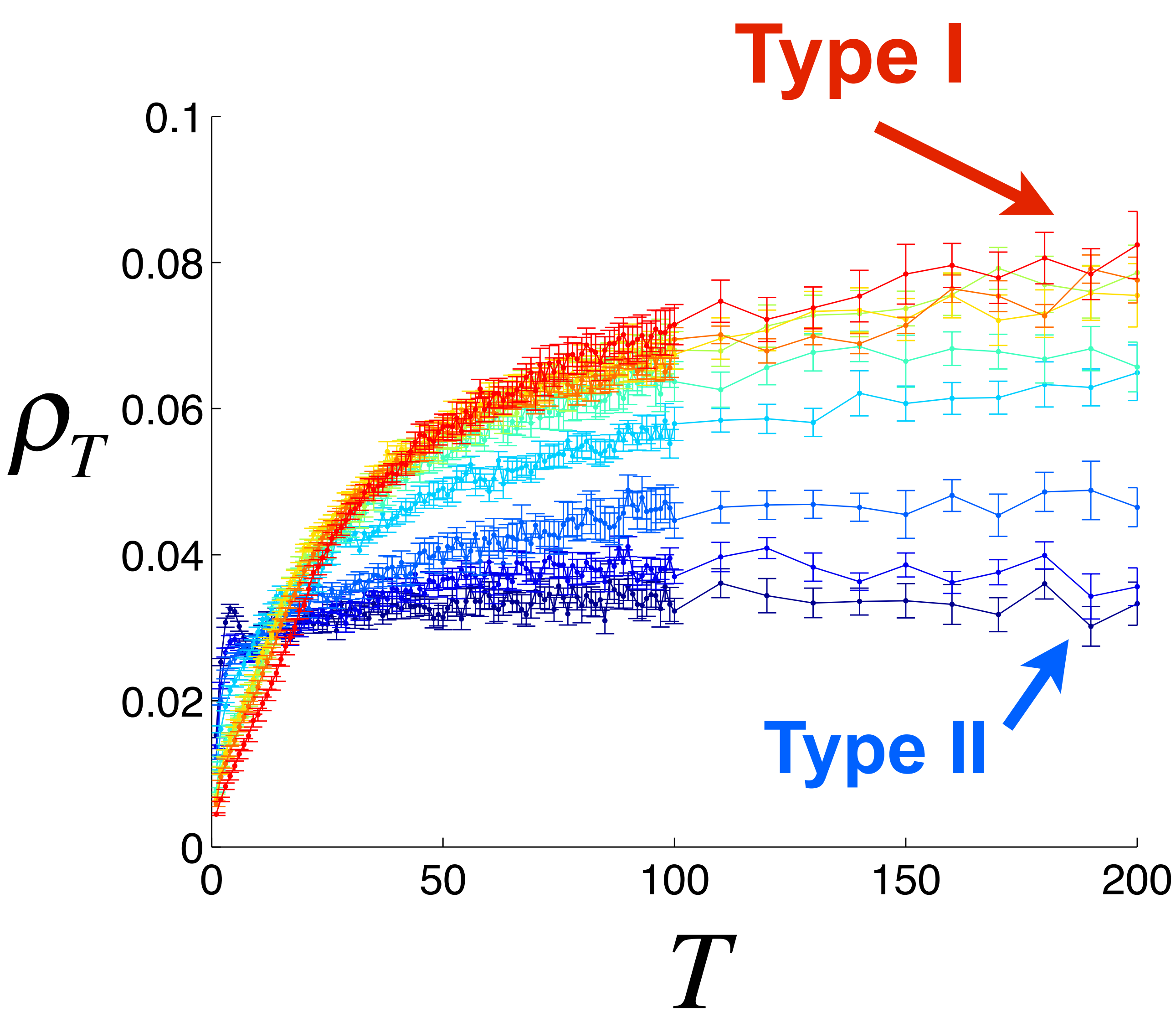
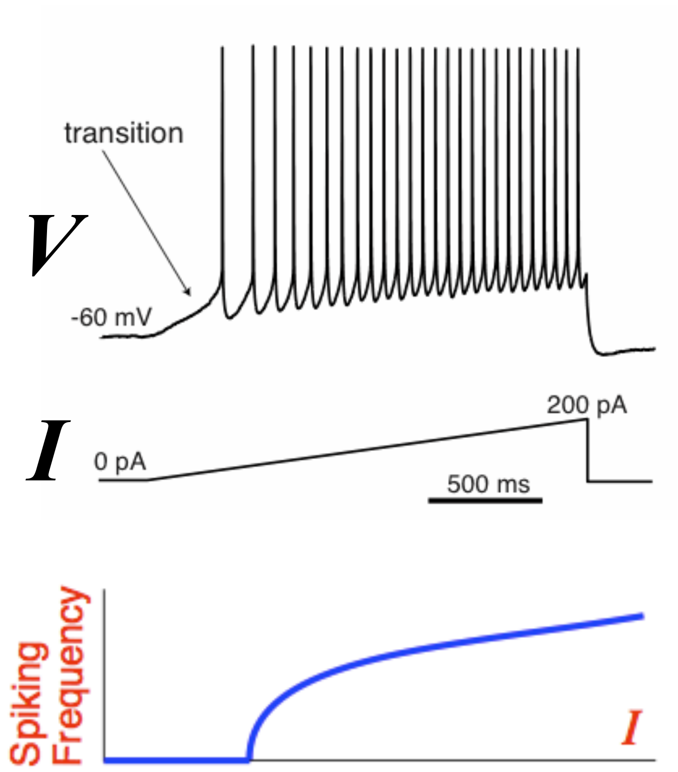


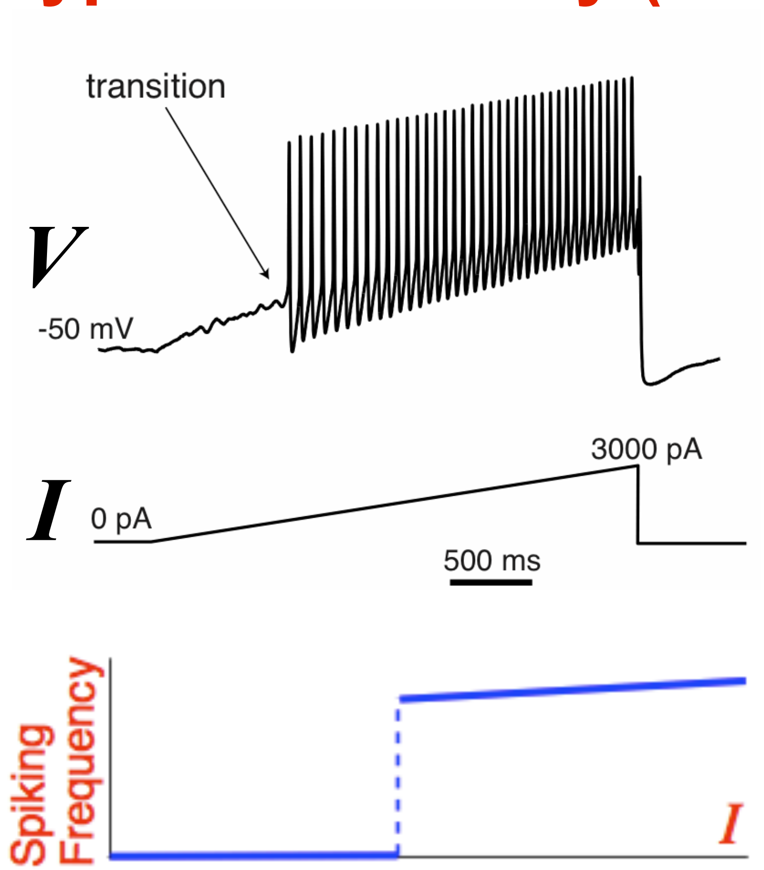
Type II cells transfer more correlation at *short* time scales; Type I cells transfer more correlation at *long* time scales

Barreiro et al., J Neurophysiology 2012

How can we understand this mathematically?
Reduced model for ODEs near a limit cycle



Type I excitability (SNIC)



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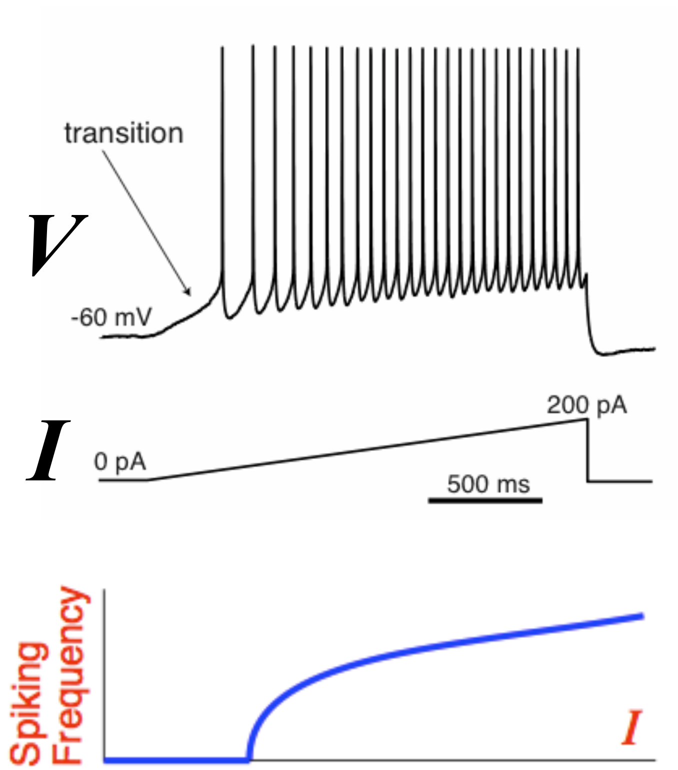
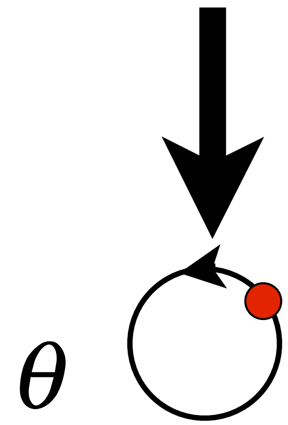
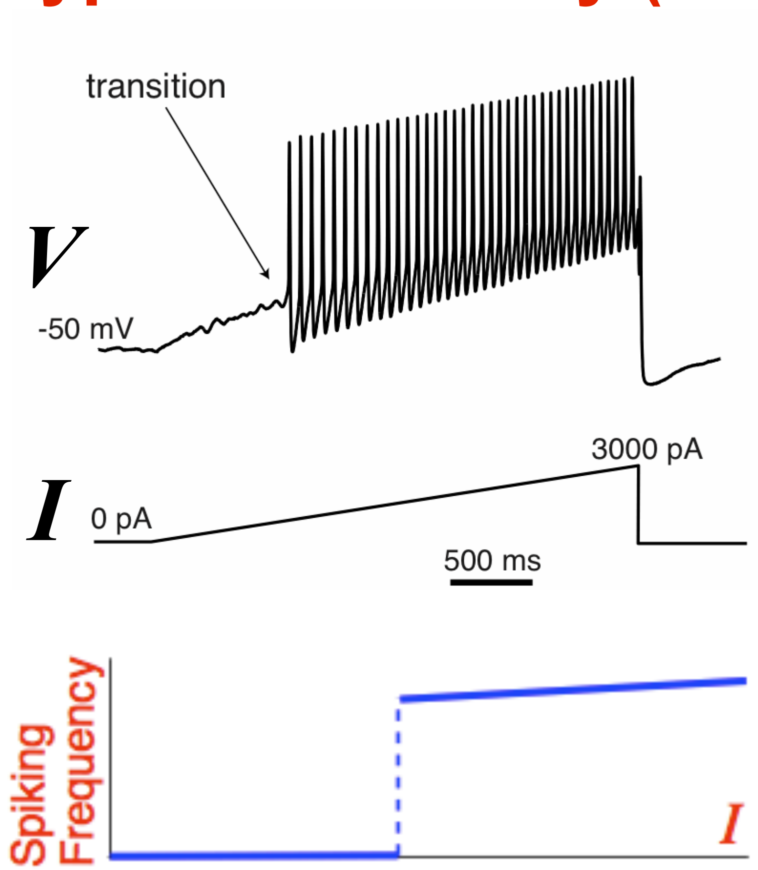


Type I excitability (SNIC)

If the neuron is firing periodically ("tonic" firing)





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$$\frac{\partial\theta}{\partial t} = \omega + Z(\theta) I_{fluc}(t)$$

$\theta = 2\pi \rightarrow$ ***spike***

$Z(\theta)$ **= phase response curve (PRC)**

phase model

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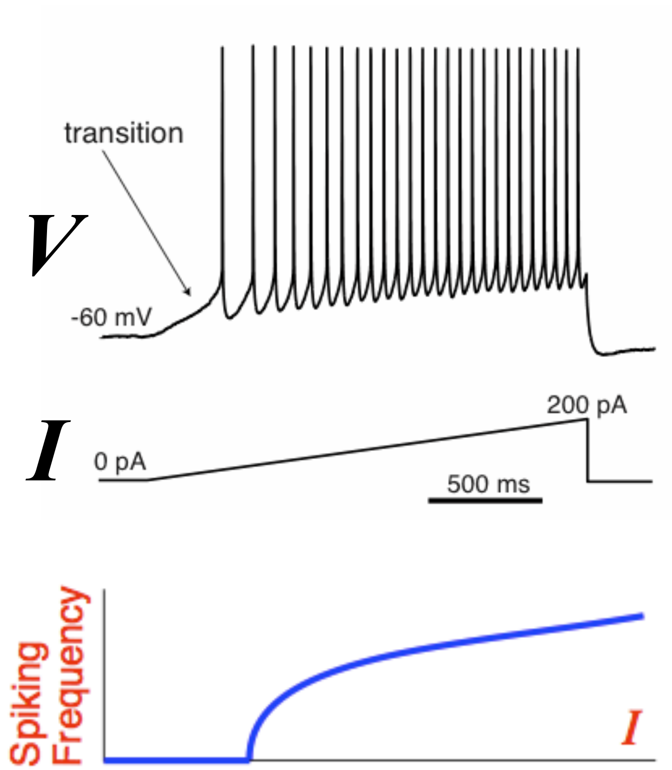

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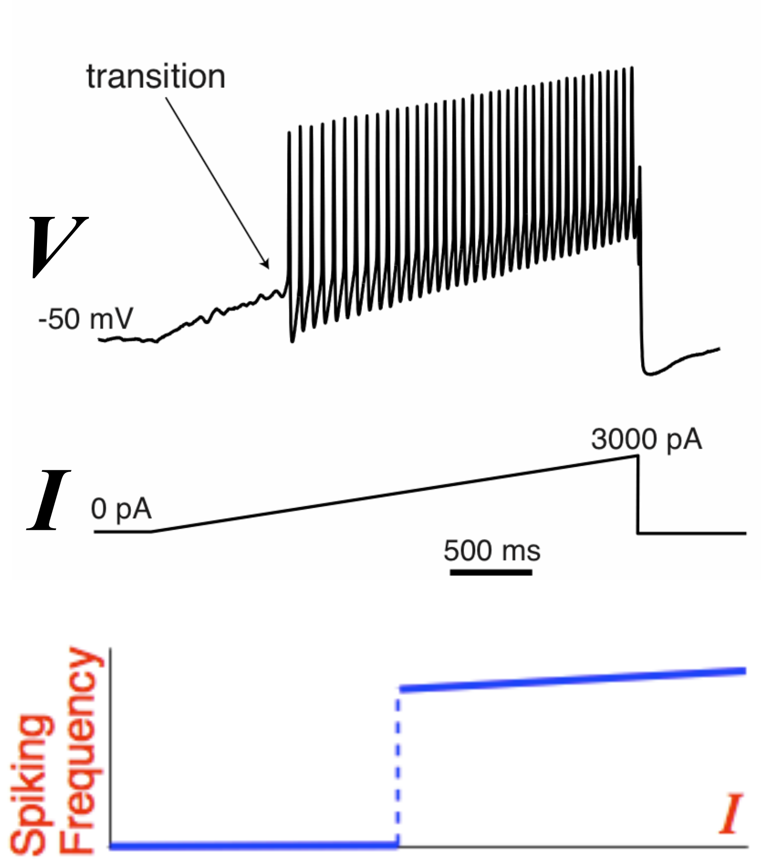

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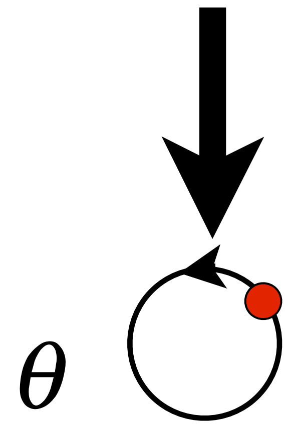

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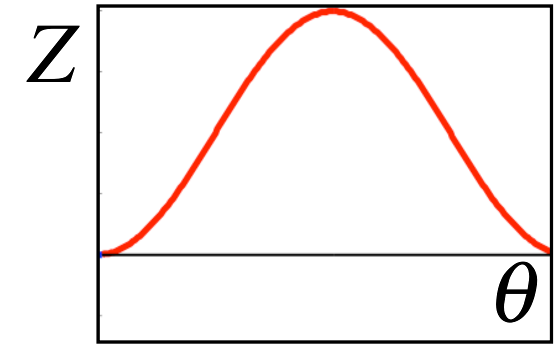
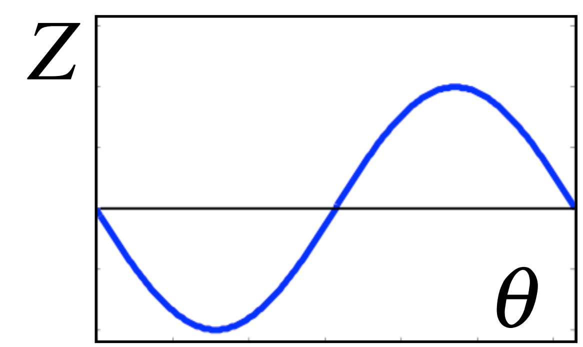


$$Z(\theta) = 1 - \cos\theta$$

Type I excitability



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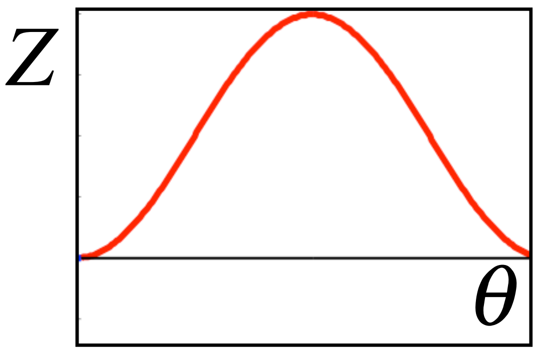
Type II excitability

Rinzel and Ermentrout '89
Ermentrout and Kopell '84
Ermentrout '96

Not just an academic exercise: PRCs can be measured (and modulated) in real neurons



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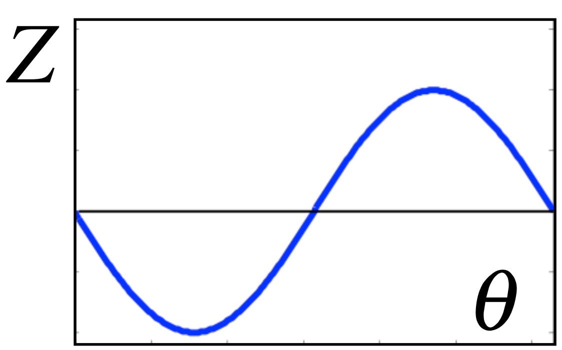

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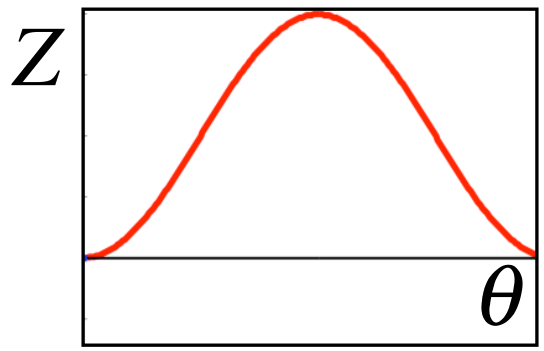

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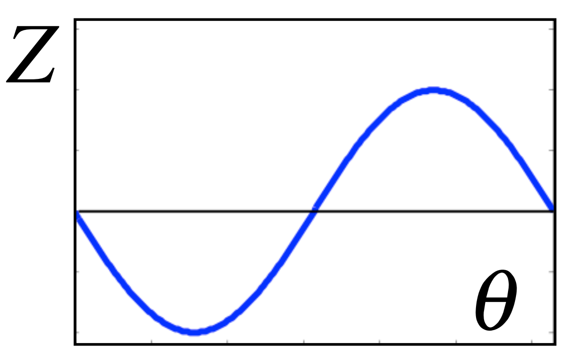

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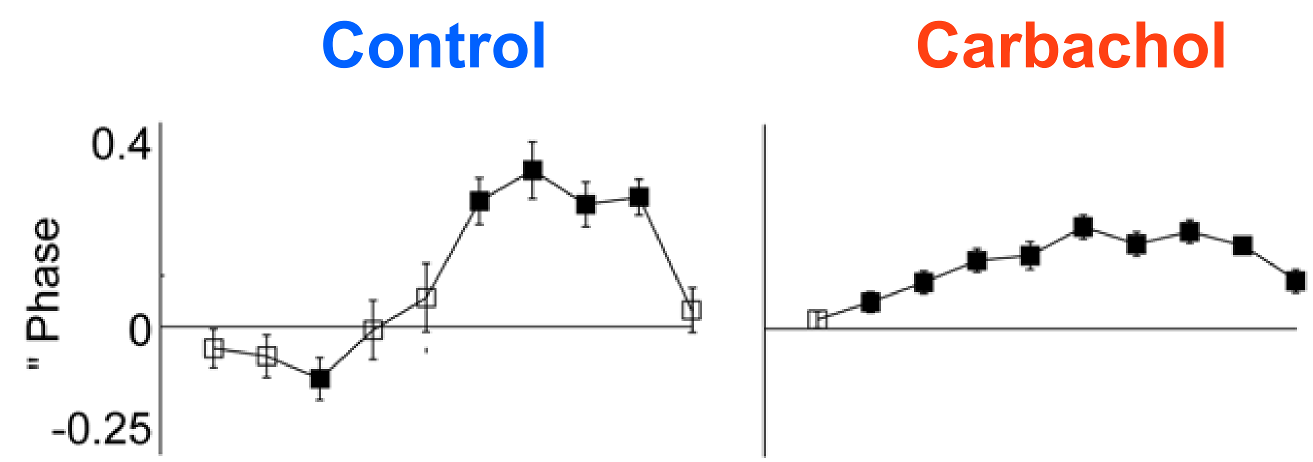
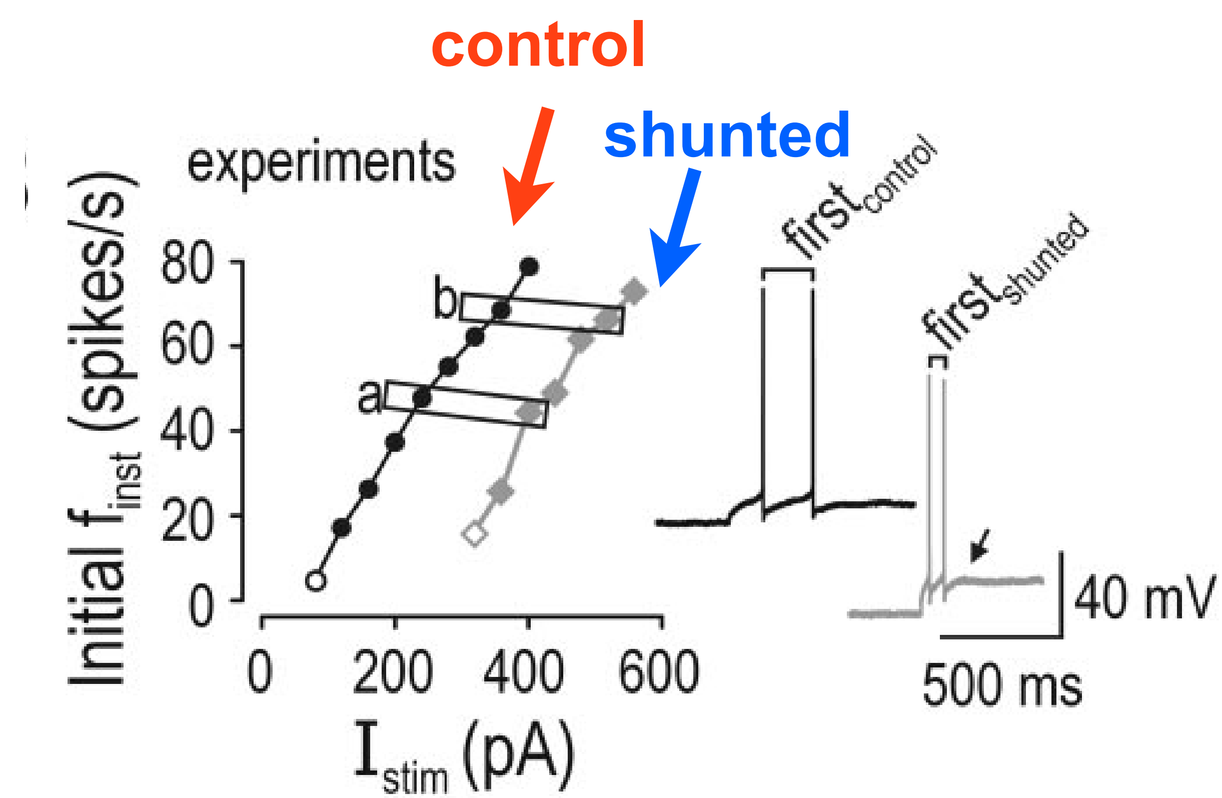


Stiefel et al., PLoS One, 2008



Prescott et al, J Neurophys, 2008

Analytical calculations in phase models

$$T \gg 1 \rightarrow \rho_T \approx c\frac{\langle Z\rangle^2}{\langle Z^2\rangle} = cS$$

but

$$T \ll 1, \rho \approx cT\left(1-\frac{\langle Z\rangle^2}{\langle Z^2\rangle}\right) = cT(1-S)$$

Marella and Ermentrout, PRE, 2008
Barreiro et al., PRE, 2010
Abouzeid and Ermentrout, PRE, 2011
Barreiro et al., *J Neurophys 2012*

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→ ***Type I* cells are more efficient at transferring correlated input at *long* time scales, *Type II* at *short* time scales.**

Marella and Ermentrout, PRE, 2008
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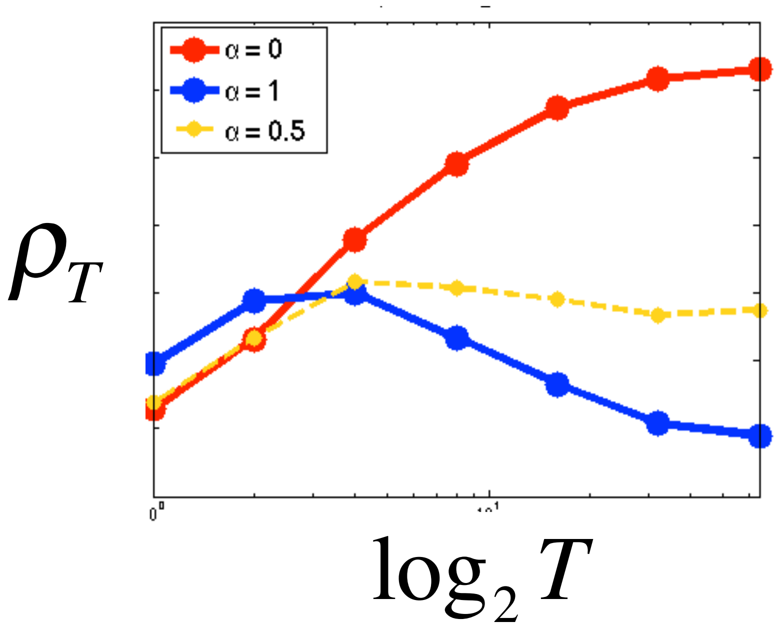
***Type I* cells are more efficient at transferring correlated input at *long* time scales, *Type II* at *short* time scales.**

In sinusoidal phase oscillators:



Marella and Ermentrout, PRE, 2008
Barreiro et al., PRE, 2010
Abouzeid and Ermentrout, PRE, 2011
Barreiro et al., *J Neurophys 2012*

Analytical calculations in phase models

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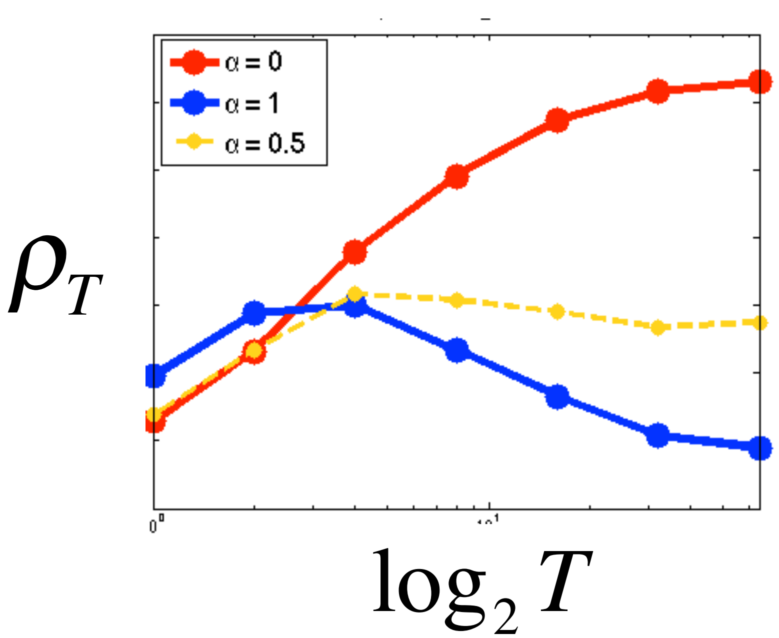

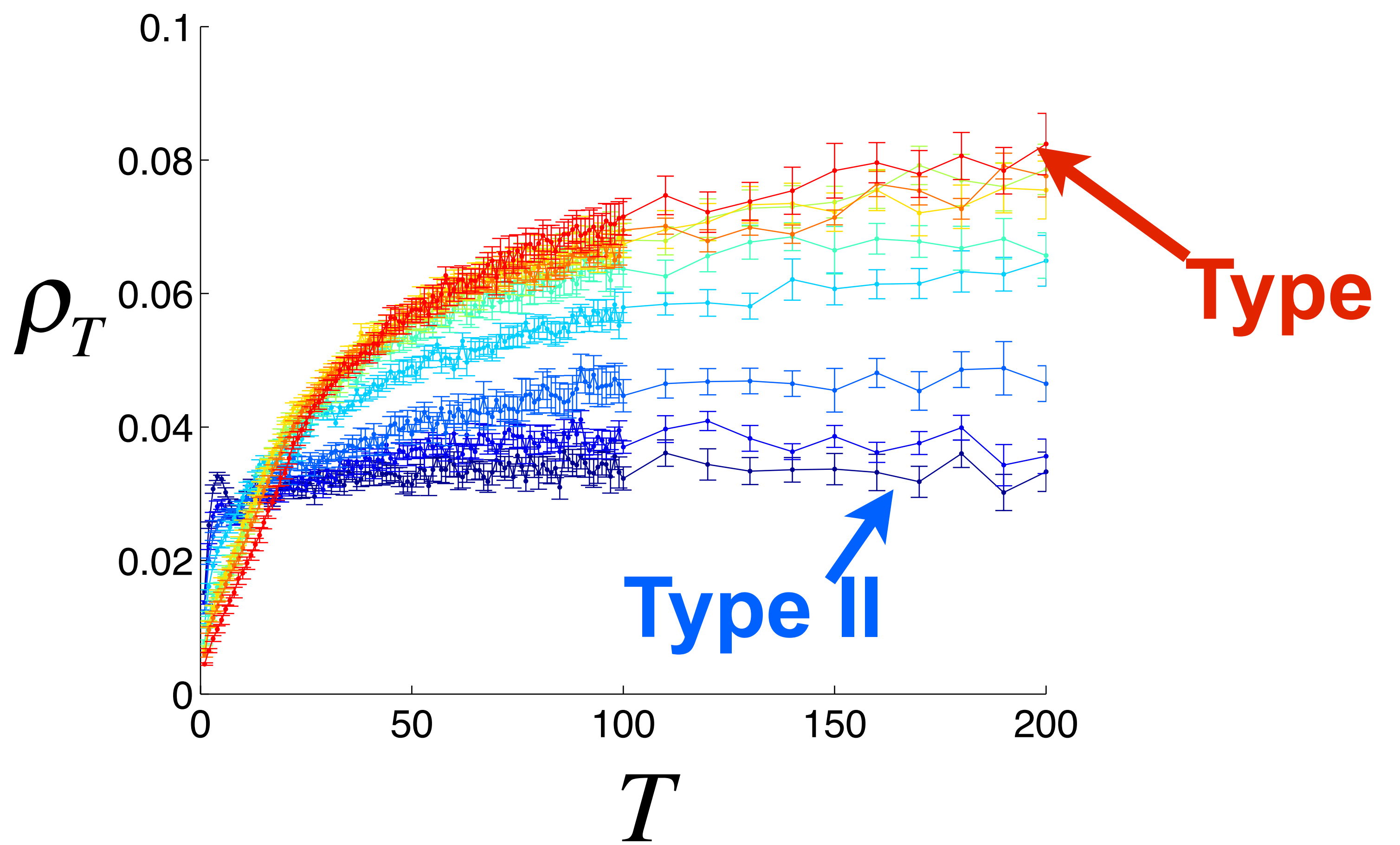

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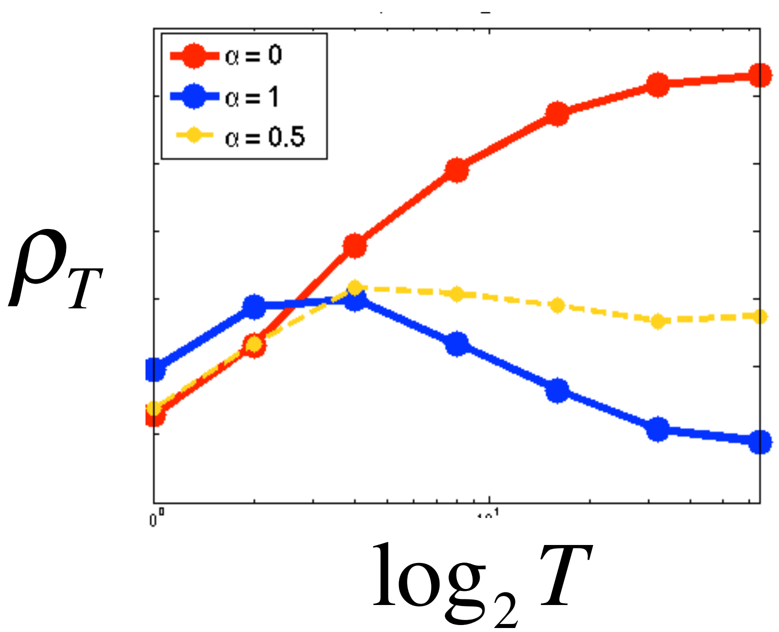
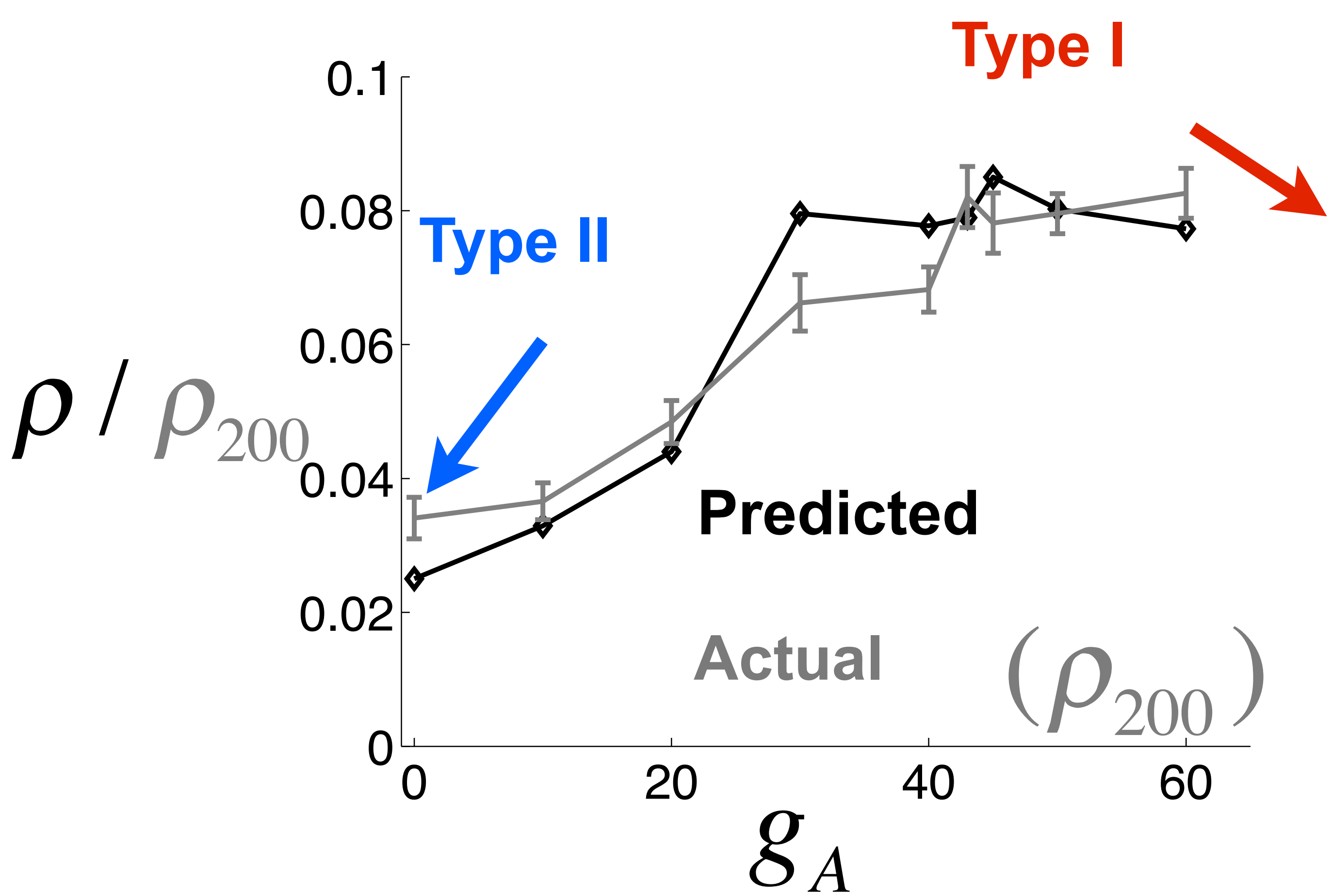




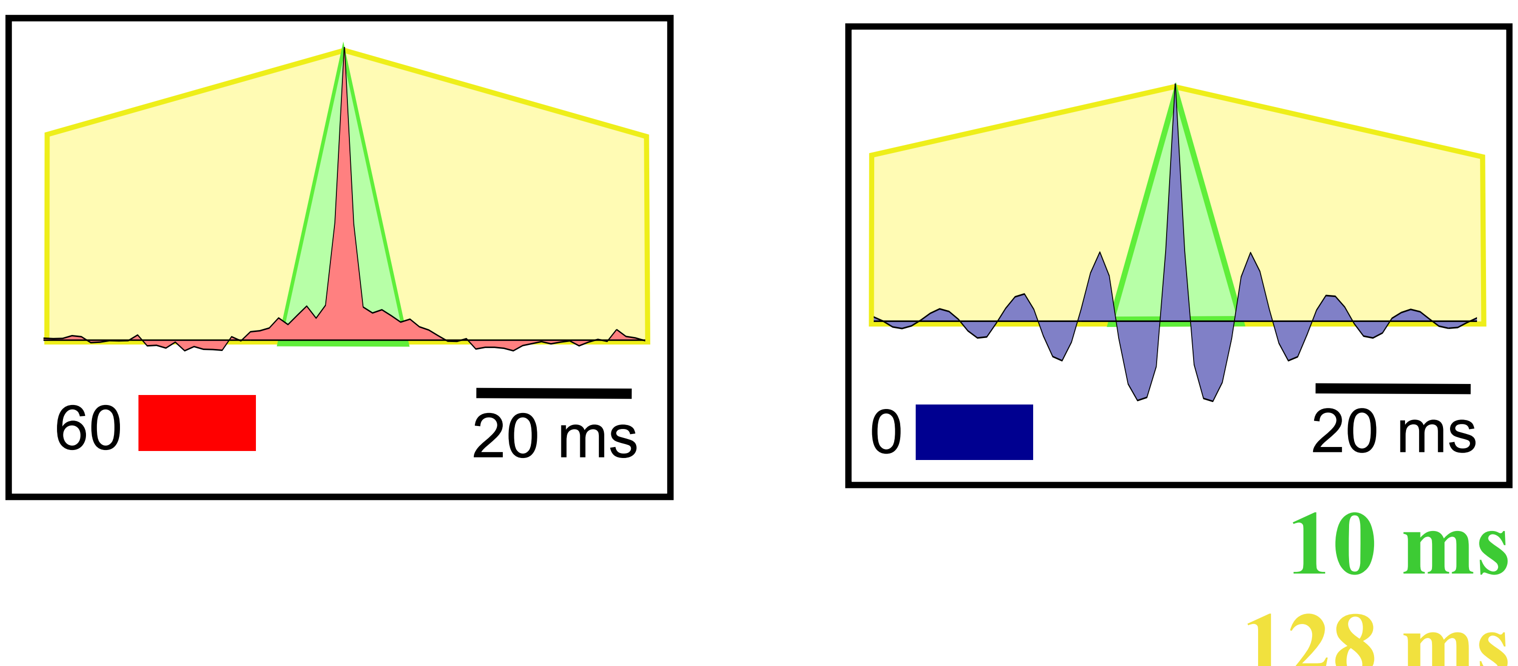
Ermentrout et al., PRE, 2008
Barreiro et al., PRE, 2010
Abouzeid and Ermentrout, PRE, 2011
Barreiro et al., *J Neurophys 2012*

Another prediction tool:
Use common input *spike-triggered average (STA)*

$$Cov_T(n_1,n_2) = T\int_{-T}^{T} C_{12}(t)\left(1-\frac{t}{T}\right)dt$$

$$C_{12}(t) \propto c\left(K * \tilde{K}\right)(t); \quad K(t) = STA(t), \tilde{K} = STA(-t)$$

$$STA(t) = \frac{1}{N_{sp}}\sum_{k=1}^{N_{sp}} I_c(t_k - t)$$



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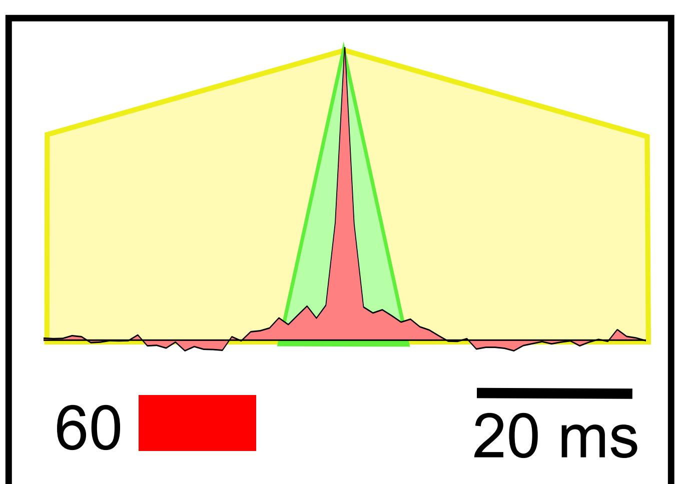
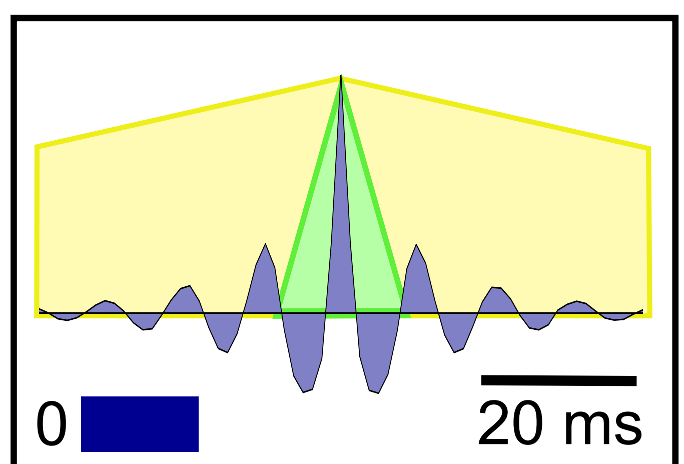
Bair et al. 2001,
Gabbiani and Koch 1998,
Ostojic 2009;
(but see Hong et al. 2012)





10 ms
128 ms

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Use common input *spike-triggered average (STA)*

Bair et al. 2001,
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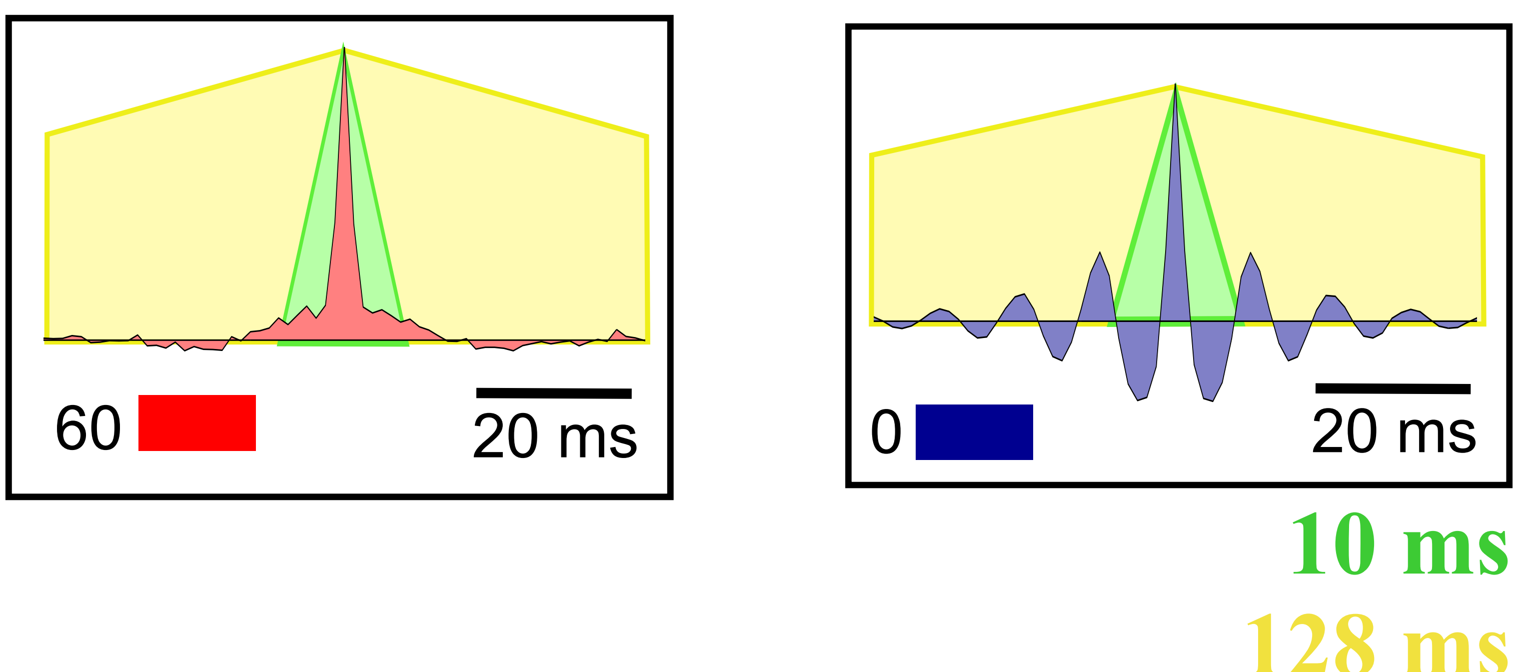
- Can be used in the subthreshold (excitable) regime
- Time window (T)-specific prediction



STA is very predictive of correlation transfer

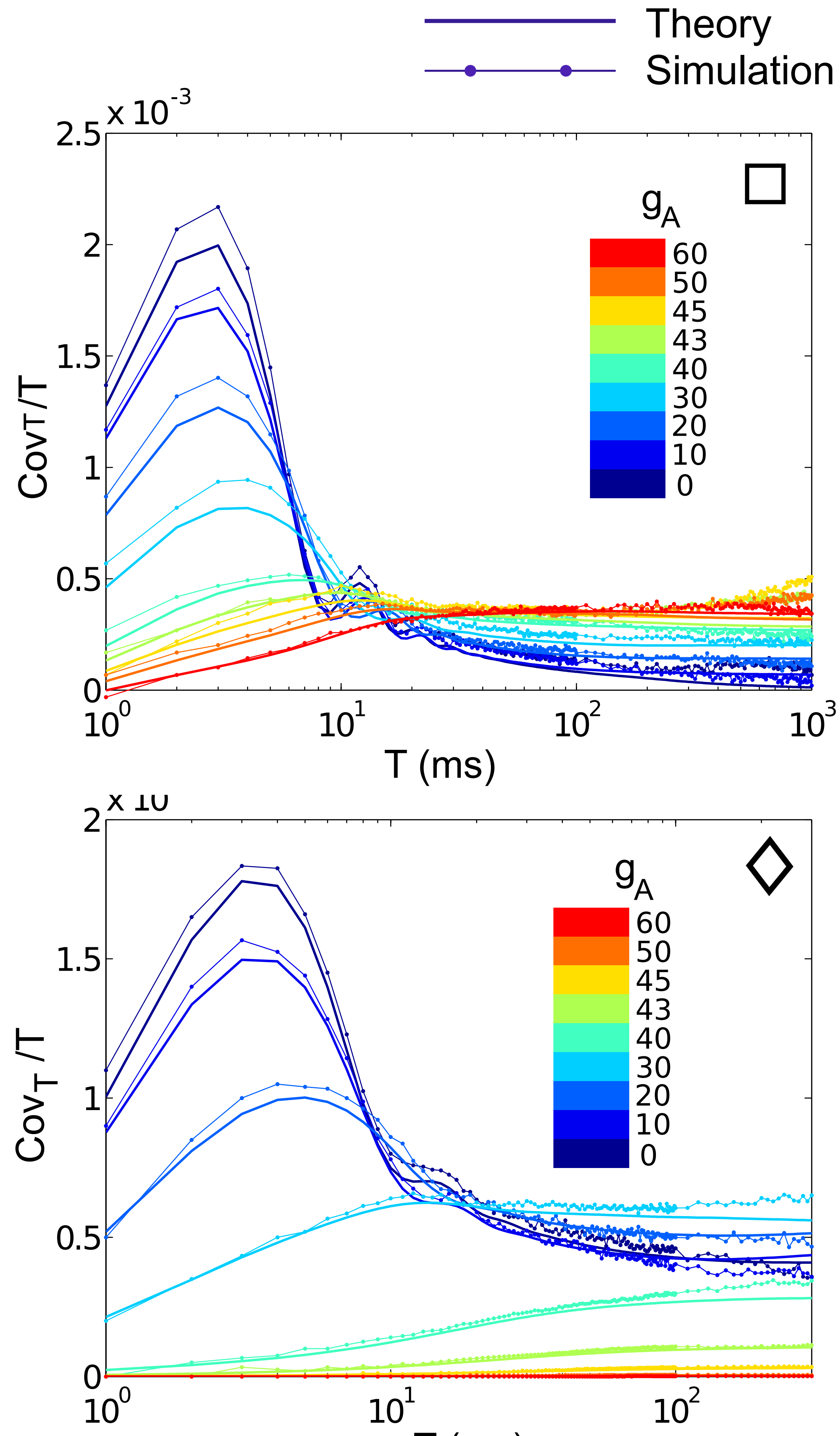
$$Cov_T(n_1,n_2) = T\int_{-T}^{T} C_{12}(t)\left(1-\frac{t}{T}\right)dt$$

$$C_{12}(t) \propto c\left(K * \tilde{K}\right)(t);$$

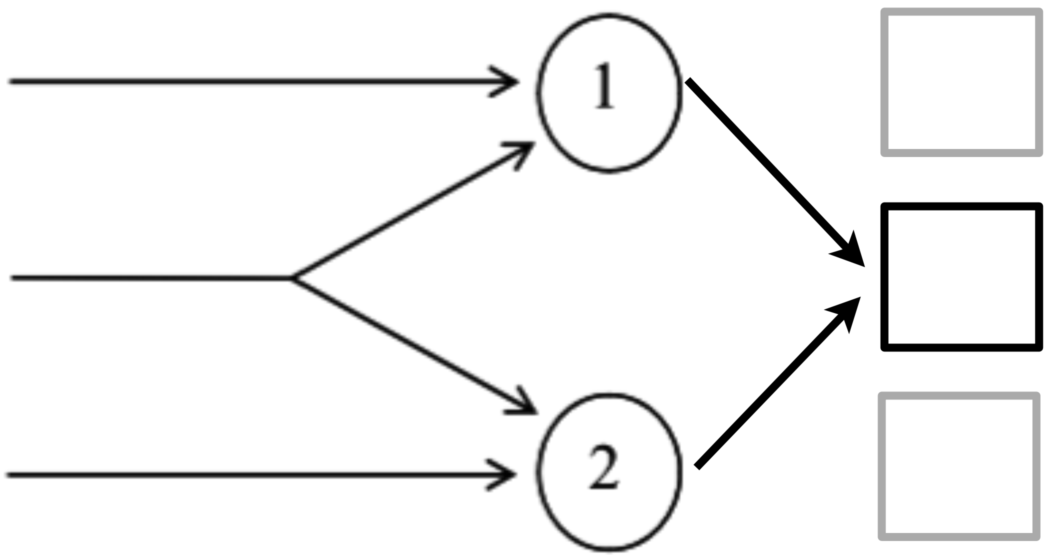
$$K(t) = STA(t), \tilde{K} = STA(-t)$$

superthreshold
(mean-driven)

subthreshold
(fluctuation-driven)



Correlation transfer modulates downstream firing rate



???

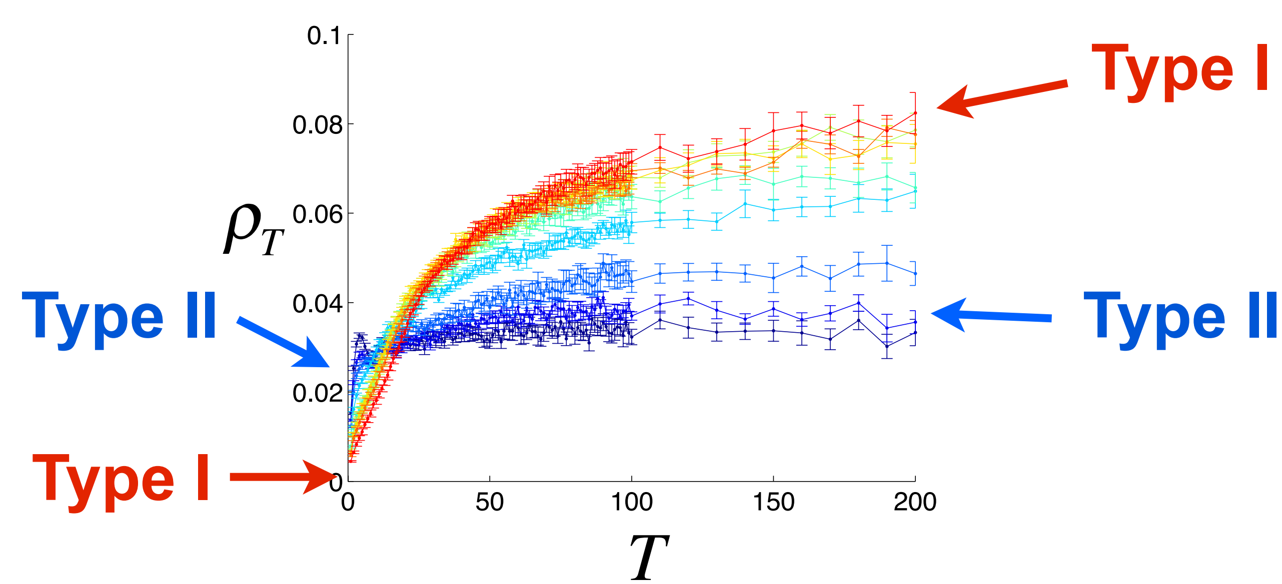
$$\tau \dot{V} = -V + I(t)$$

"Hears" $\sum_i n_i^{(\tau)}$ ..... larger fluctuations in this sum trigger more frequent spikes

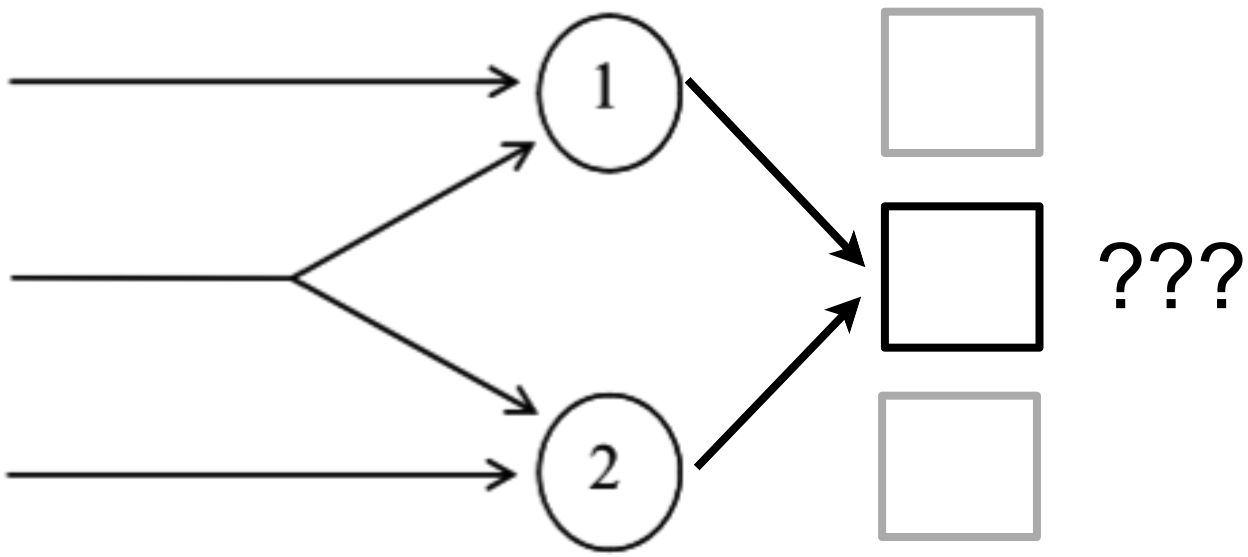
$$Var\left(\sum_i n_i^{(\tau)}\right) \propto N^2 \rho_\tau$$

Type II cells will be more effective than Type I cells at driving *short time constant* neurons

Type I cells will be more effective than Type II cells at driving *long time constant* neurons



Modulatory effect seen across upstream operating regimes



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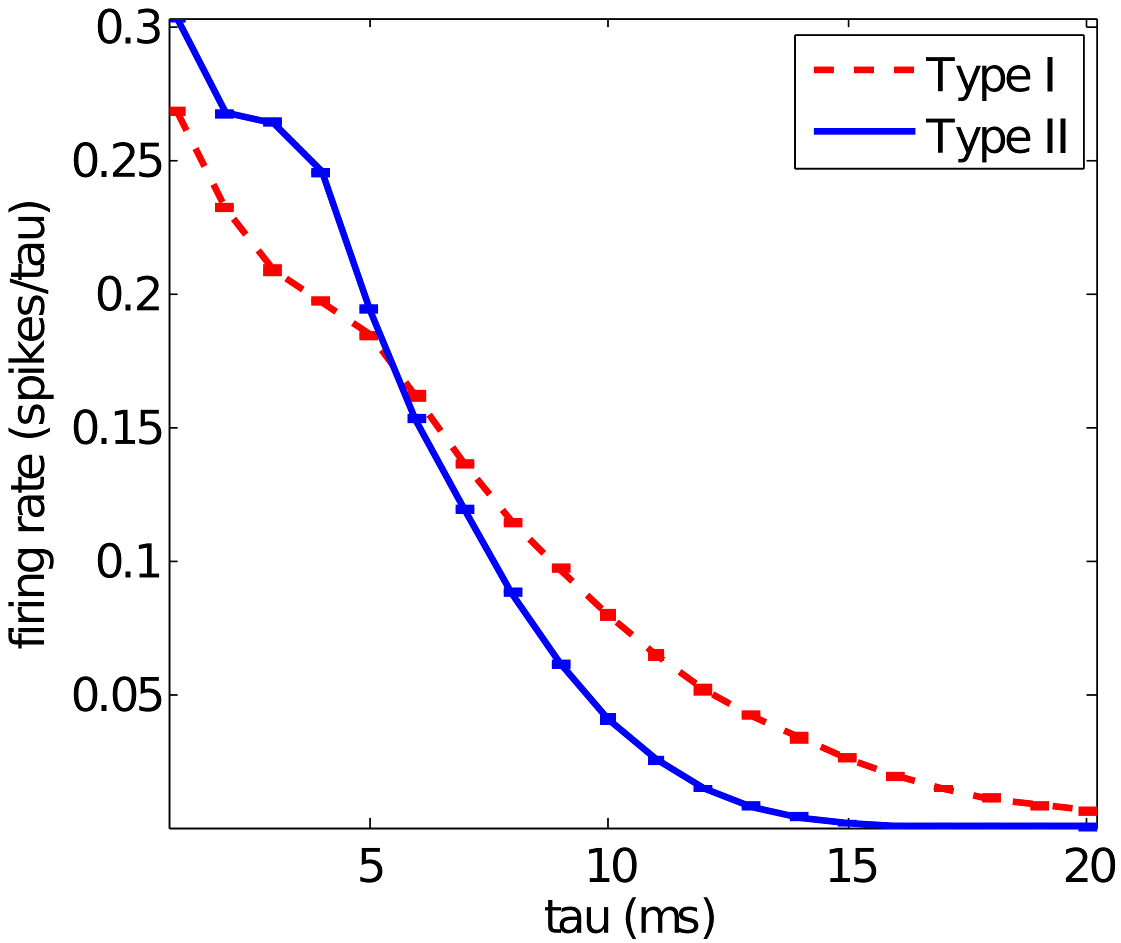
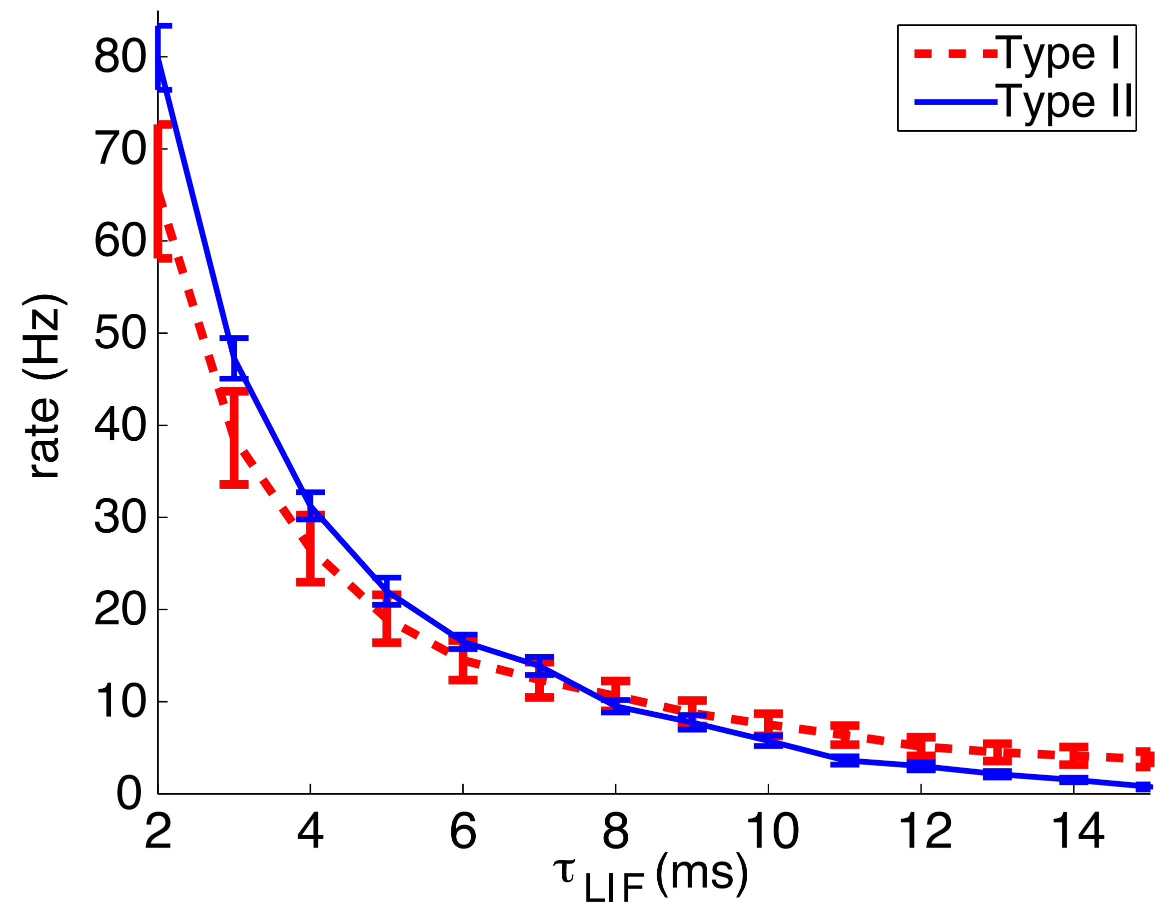
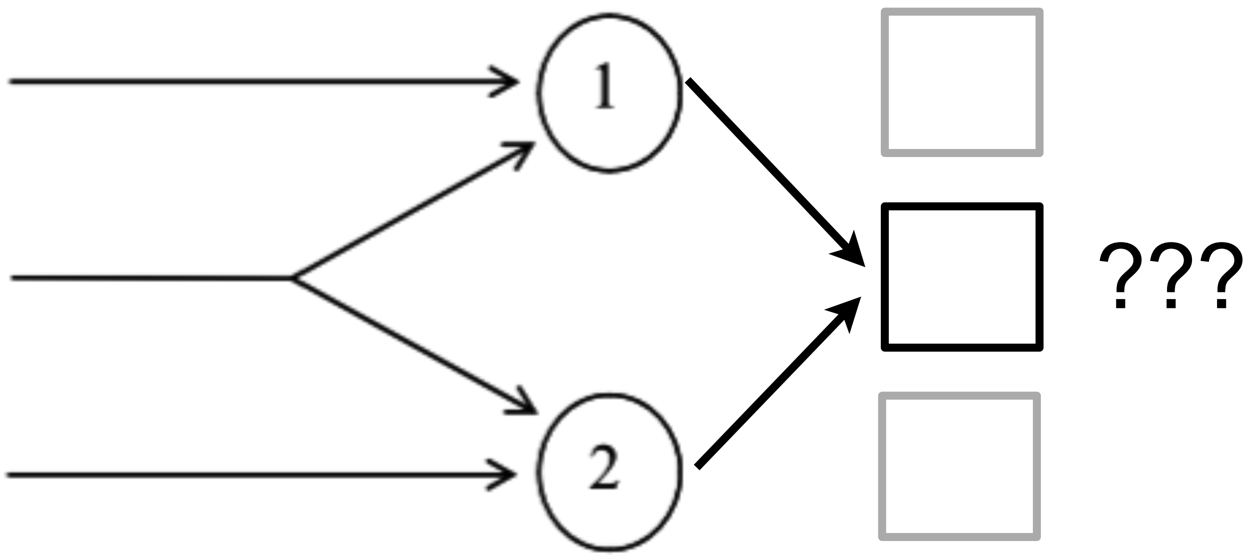


mean-driven upstream layer



fluctuation-driven upstream layer

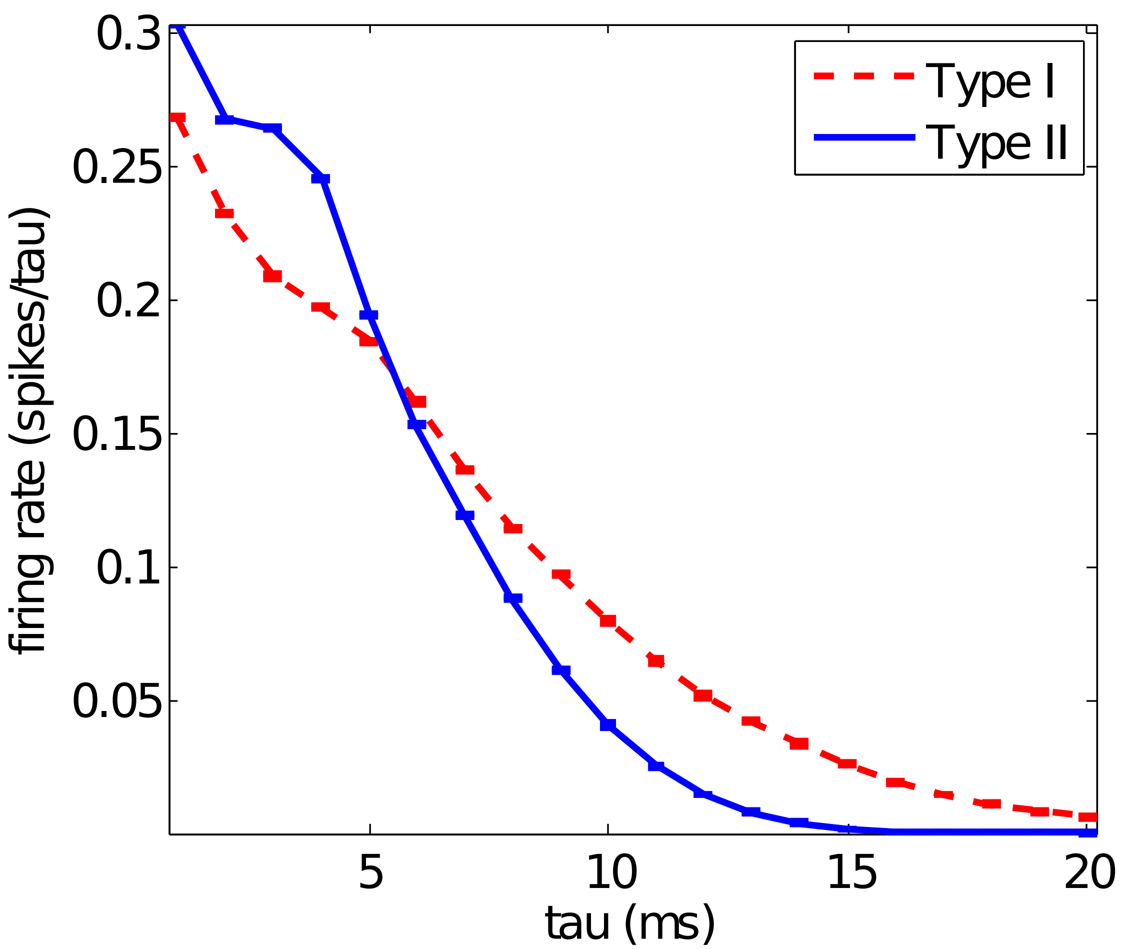
Modulatory effect seen across upstream operating regimes



$$\tau \dot{V} = -V + I(t)$$

Type I/Type II switch occurs at biophysically meaningful timescale: $\tau \sim 5 - 10 \text{ ms}$

Destexhe et al. 2003; Prescott and De Koninck 2009



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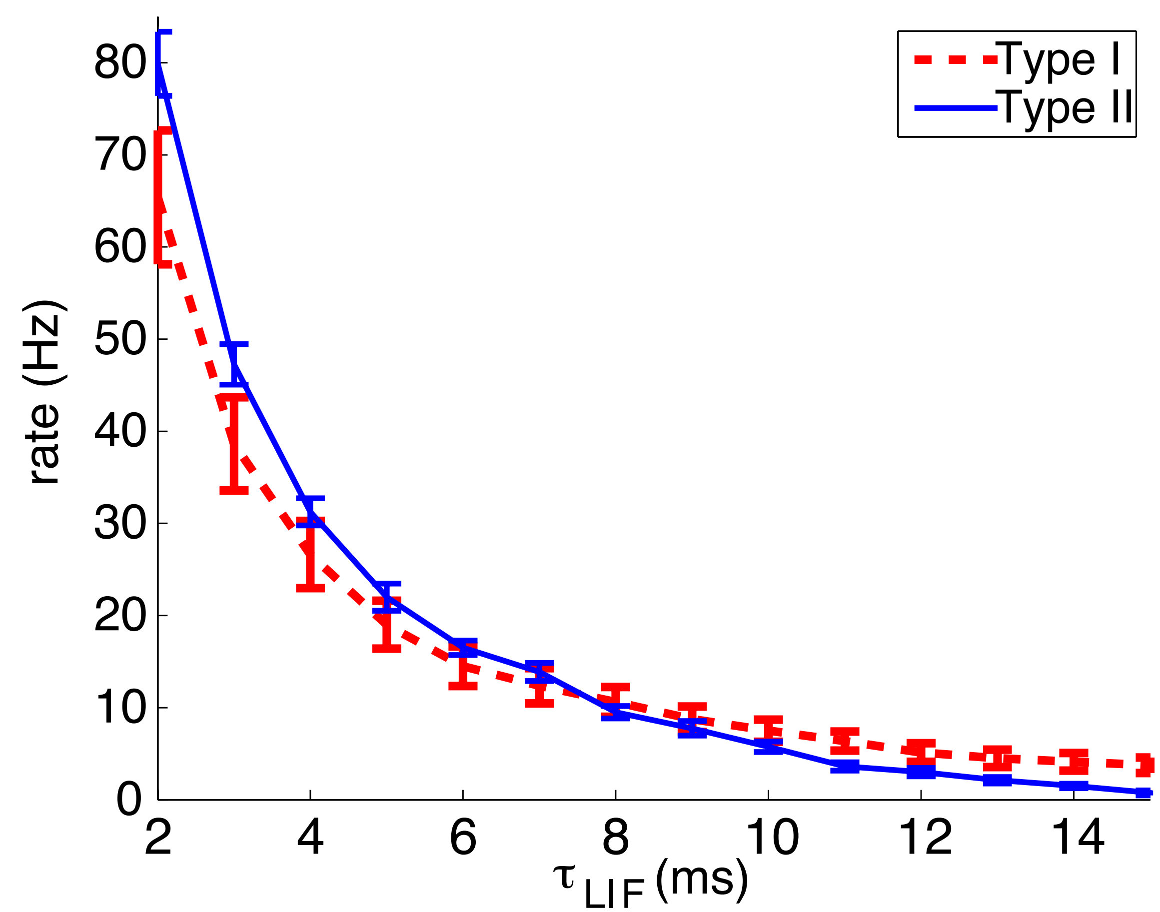


fluctuation-driven upstream layer

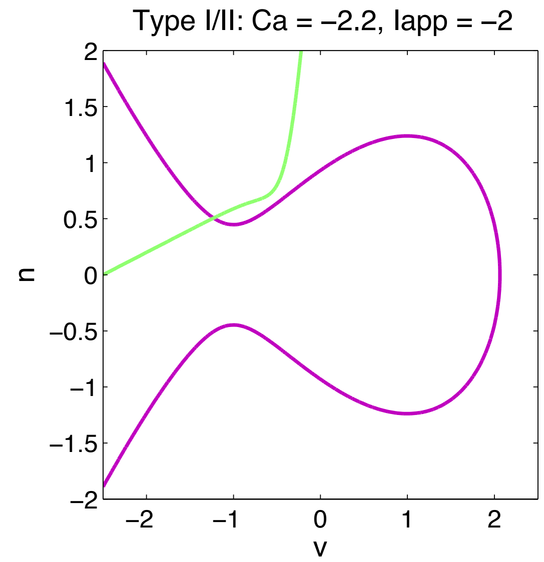
On-going work: a novel excitability mechanism: “Type IV”

$$\dot{V} = \frac{1}{\varepsilon_V}\left(V - V^3/3 + 2/3 - n^2 - z + I_{app}\right)$$

$$\dot{n} = \varepsilon_n\left(k_m\left(V - V_0\right)\left(1 + \frac{a}{1 + e^{(4k/a)(V_0 - V + 0.2)}}\right) + n_0 - n\right)$$

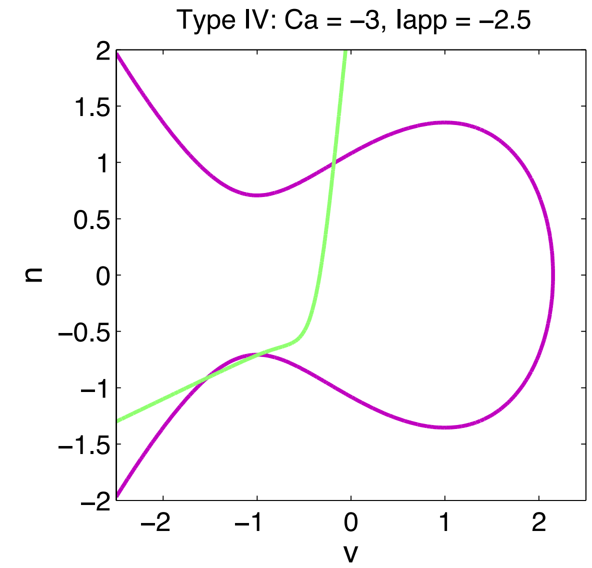
$$\dot{z} = \varepsilon_{Ca}\left(\frac{k}{1 + e^{-5(V - a_{Ca})}} - 3 - z\right); \quad \varepsilon_{Ca} \ll \varepsilon_n$$

Similar to models in:
Franci et al. *PLoS One* 2012;
Drion et al. *PLoS Comp Bio* 2012



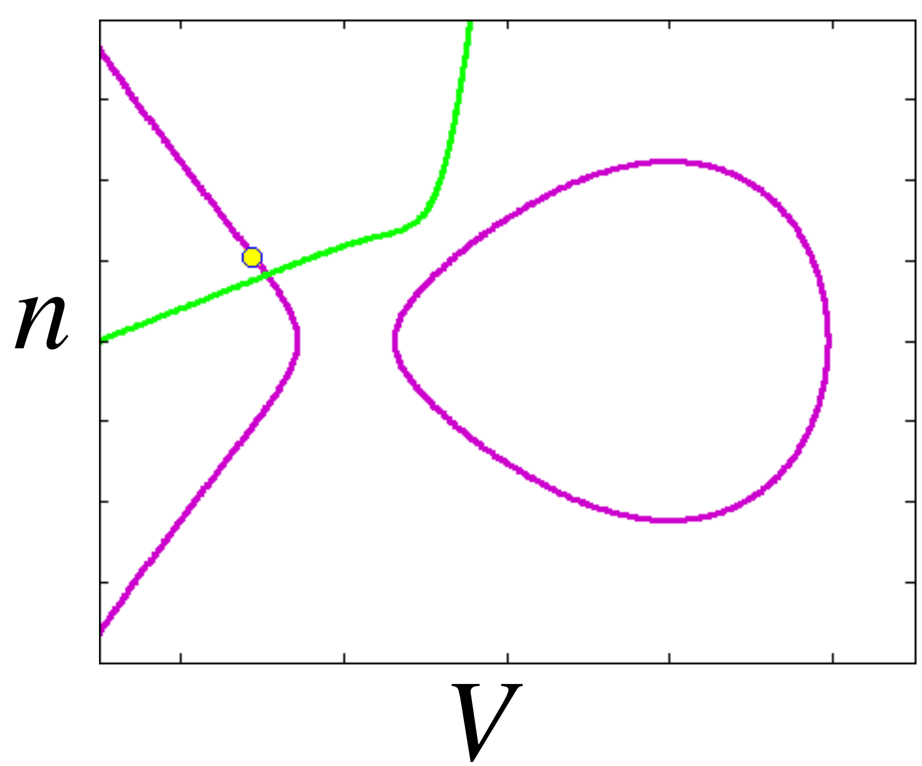
Type I/II

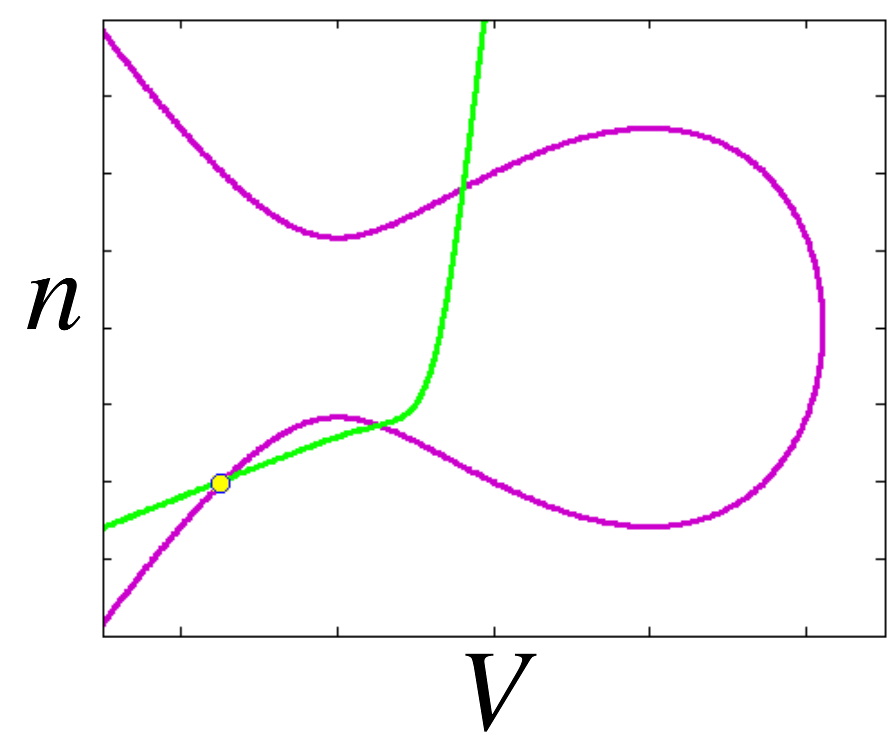
$(n_0 = 0.8)$



Type IV

$(n_0 = -0.5)$





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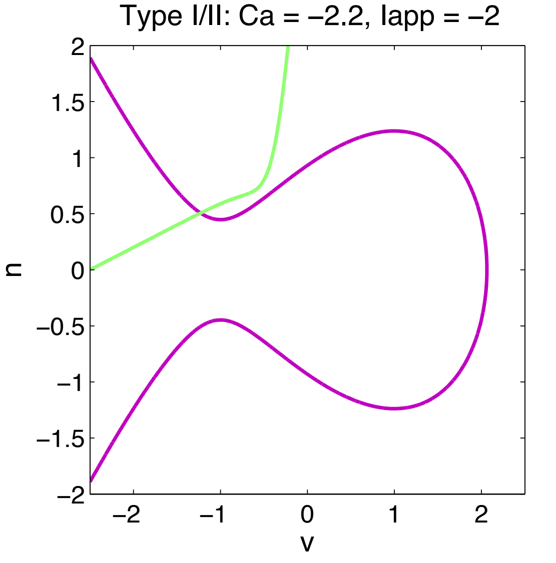

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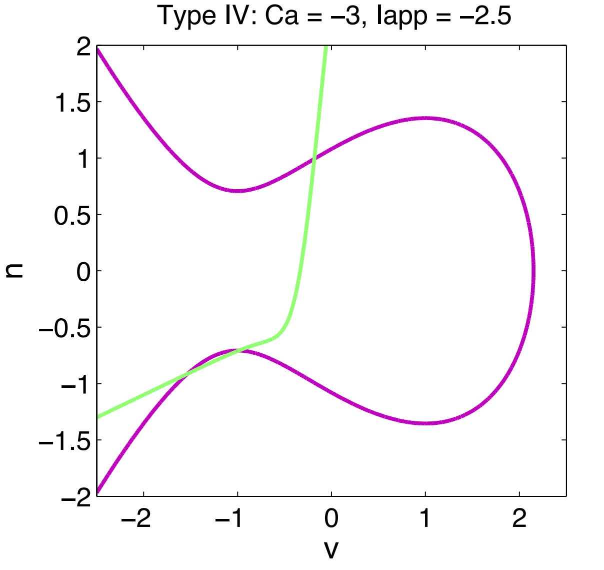

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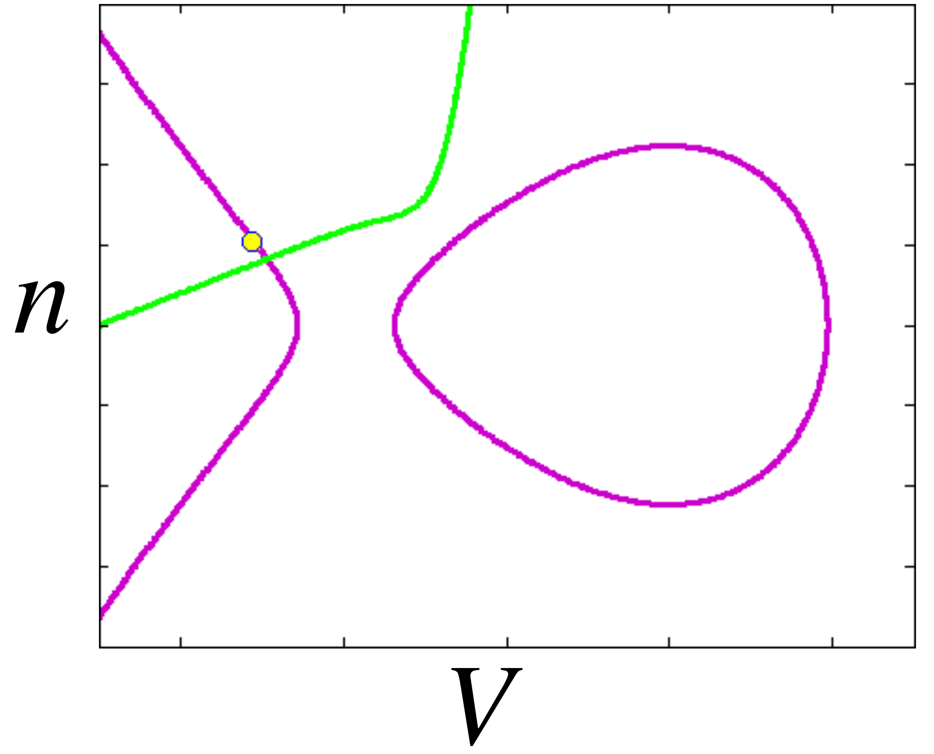

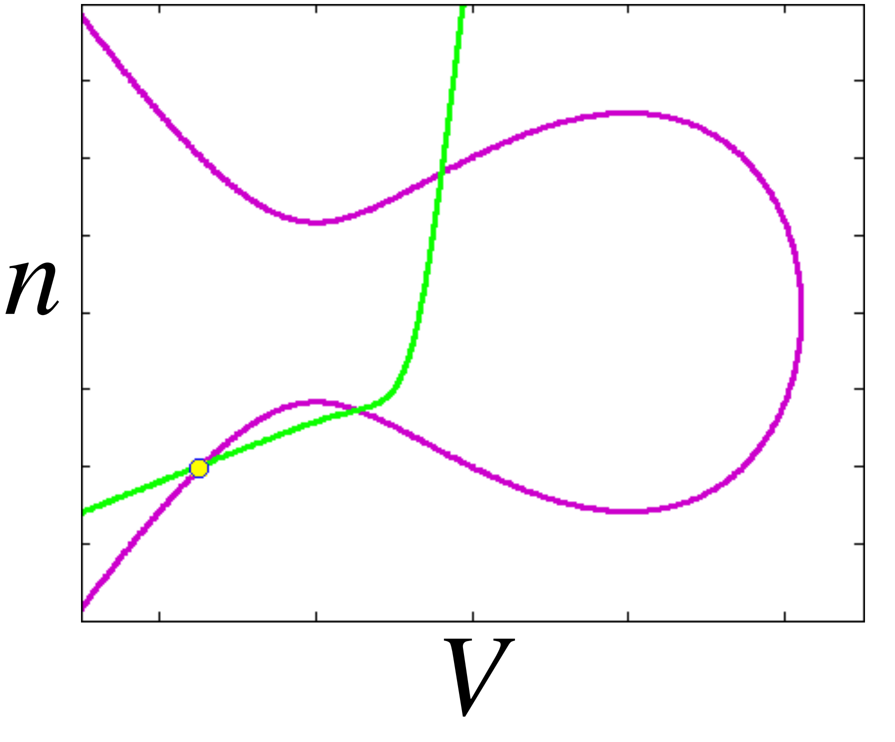

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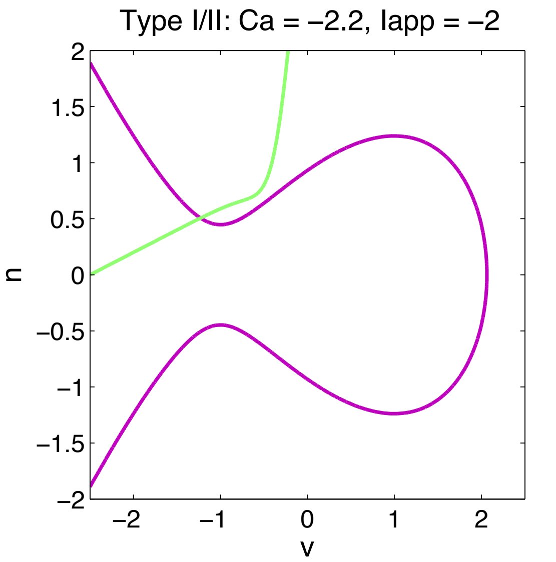

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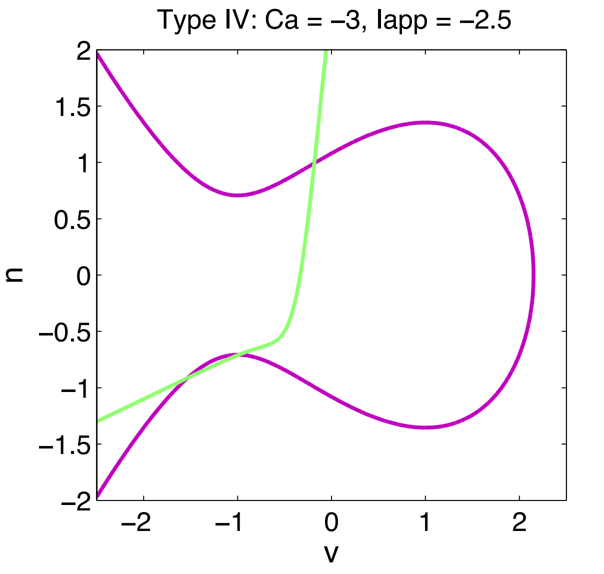

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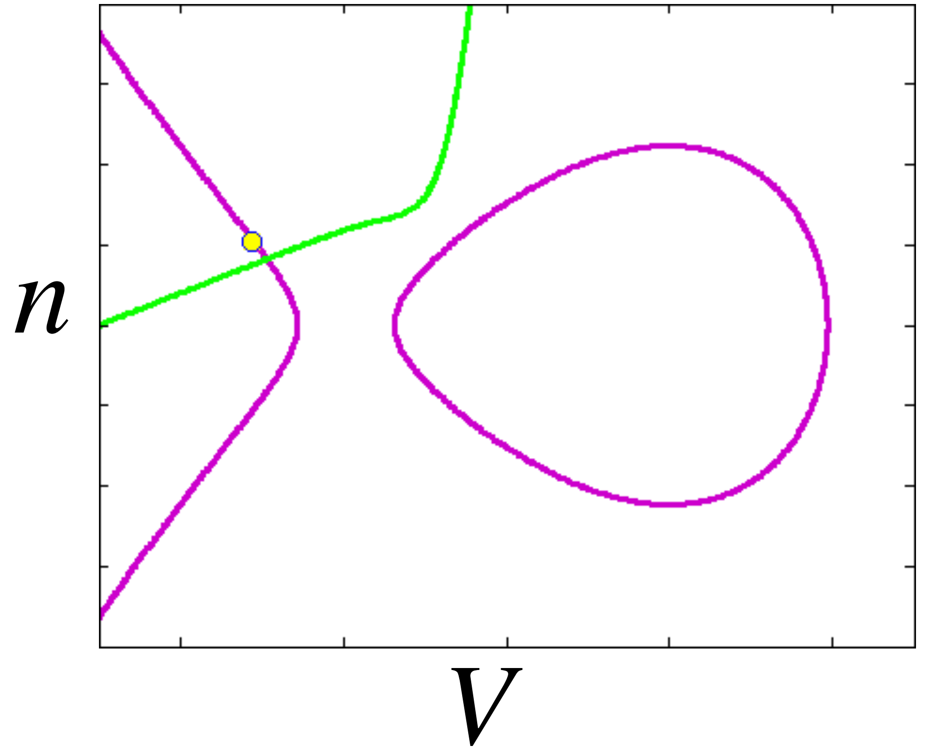
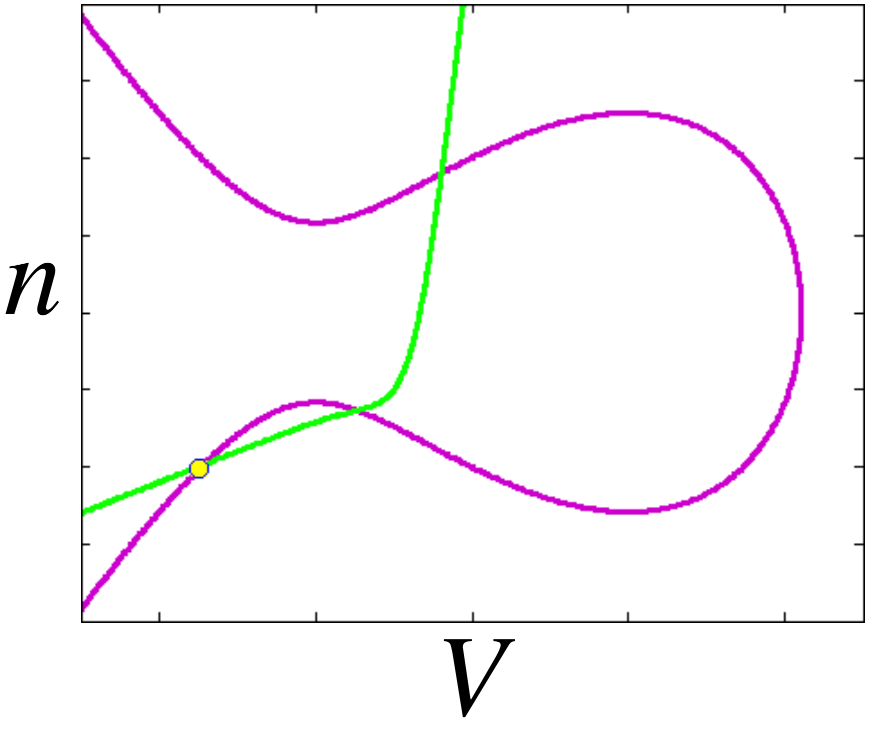
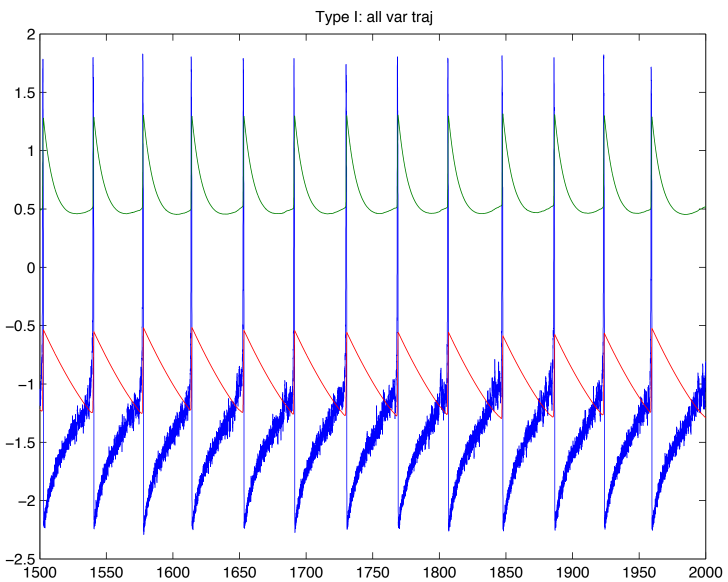
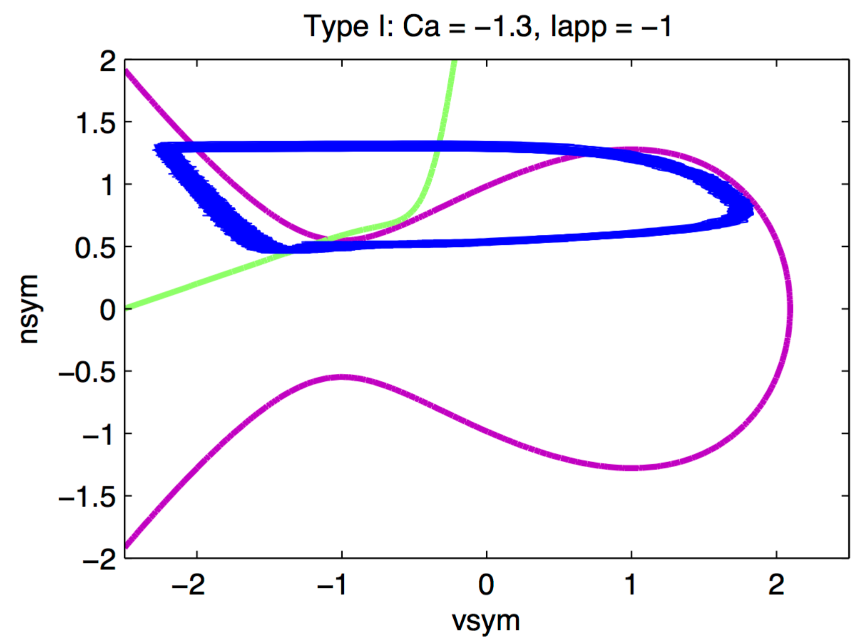


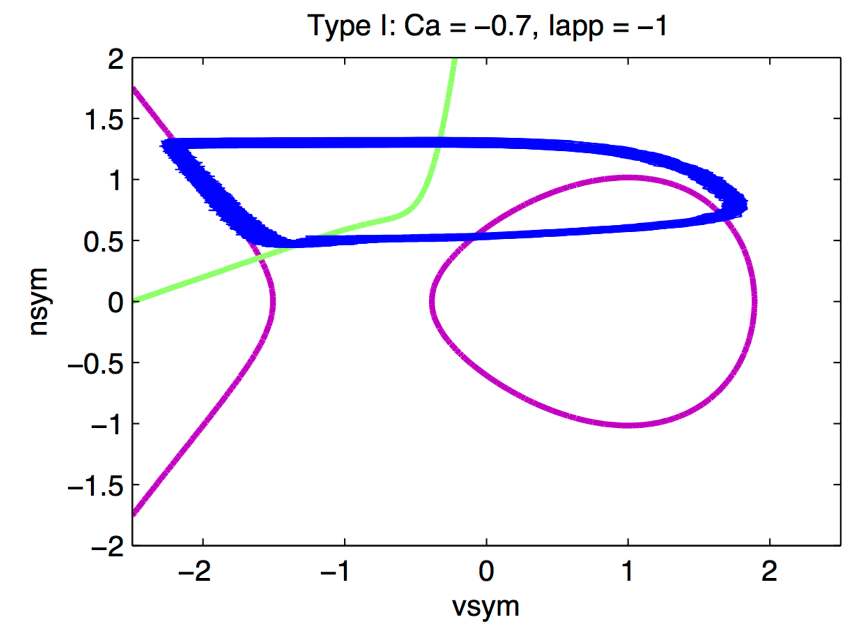


Effect of lower nullcline branch on spike shape: after-depolarization potentials (ADP)

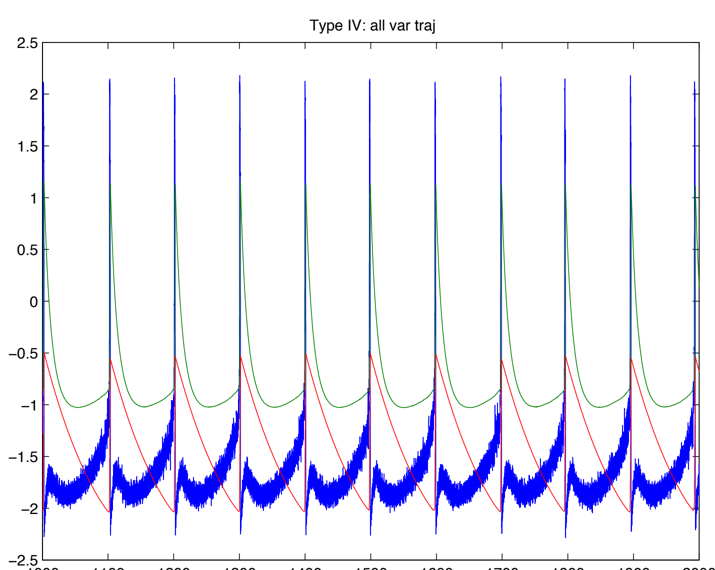
Type I/II

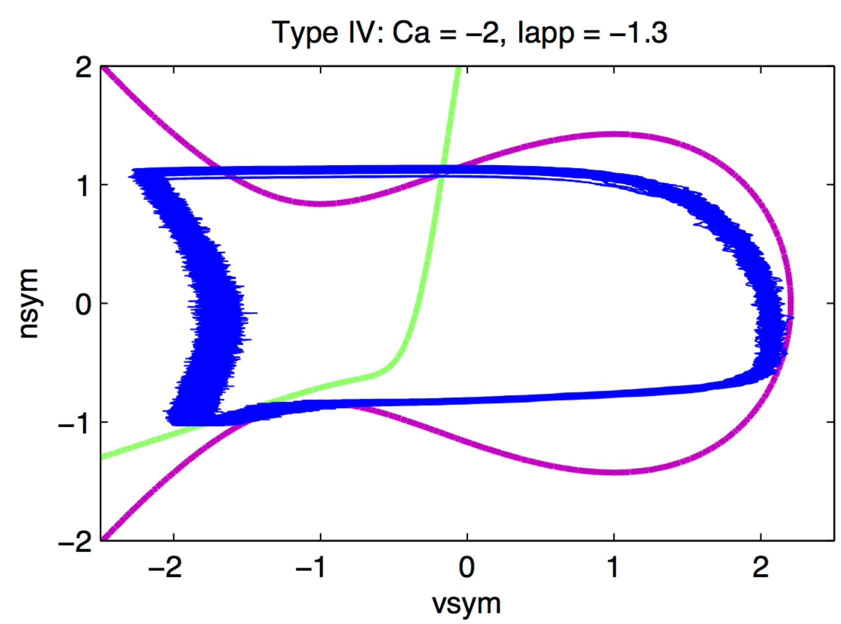


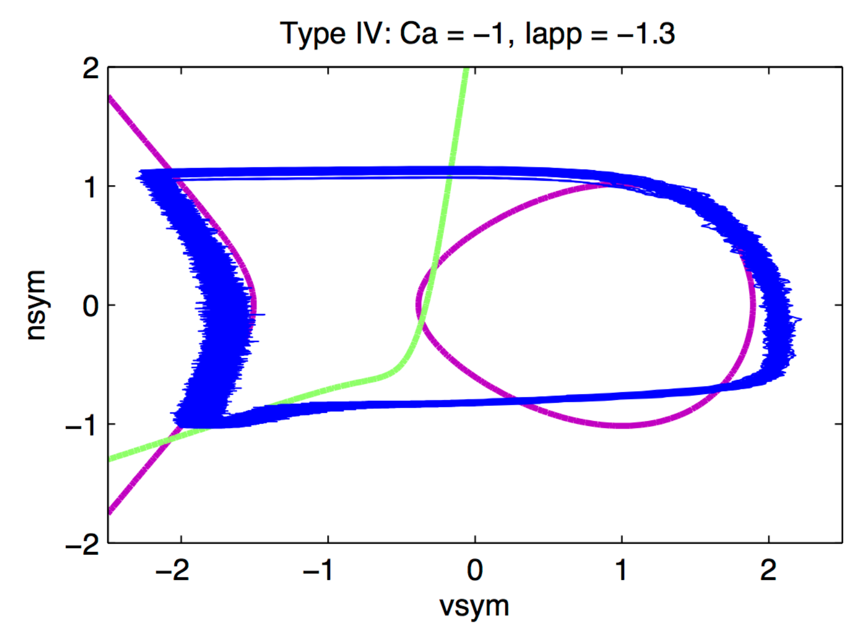




Type IV





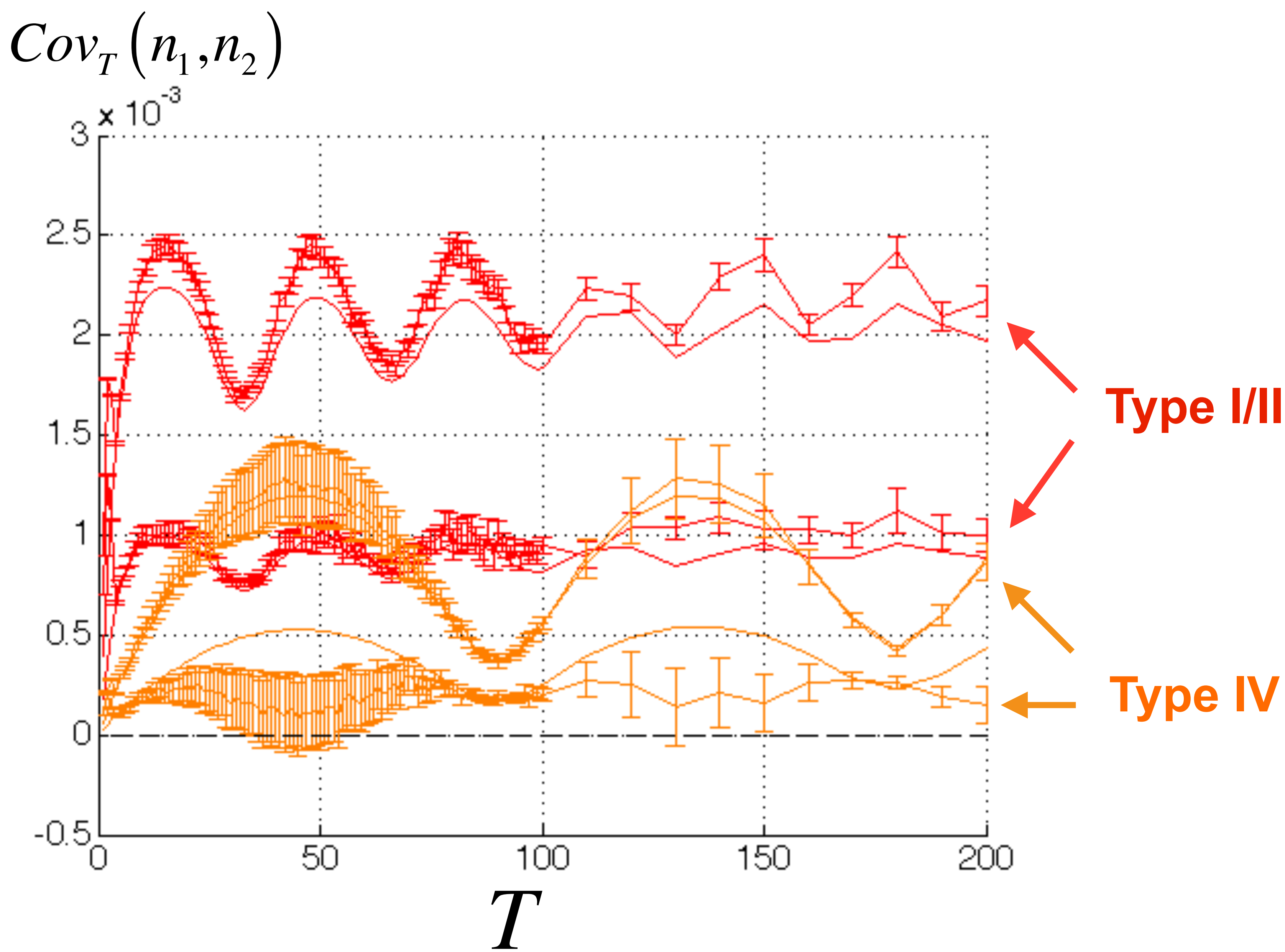


In some cases, the STA effectively predicts covariance

$$Cov_T(n_1, n_2) = T\int_{-T}^{T} C_{12}(t)\left(1 - \frac{t}{T}\right)dt$$

$$C_{12}(t) \propto c\left(K * \tilde{K}\right)(t);$$

$$K(t) = STA(t), \tilde{K} = STA(-t)$$



What about ρ_T?

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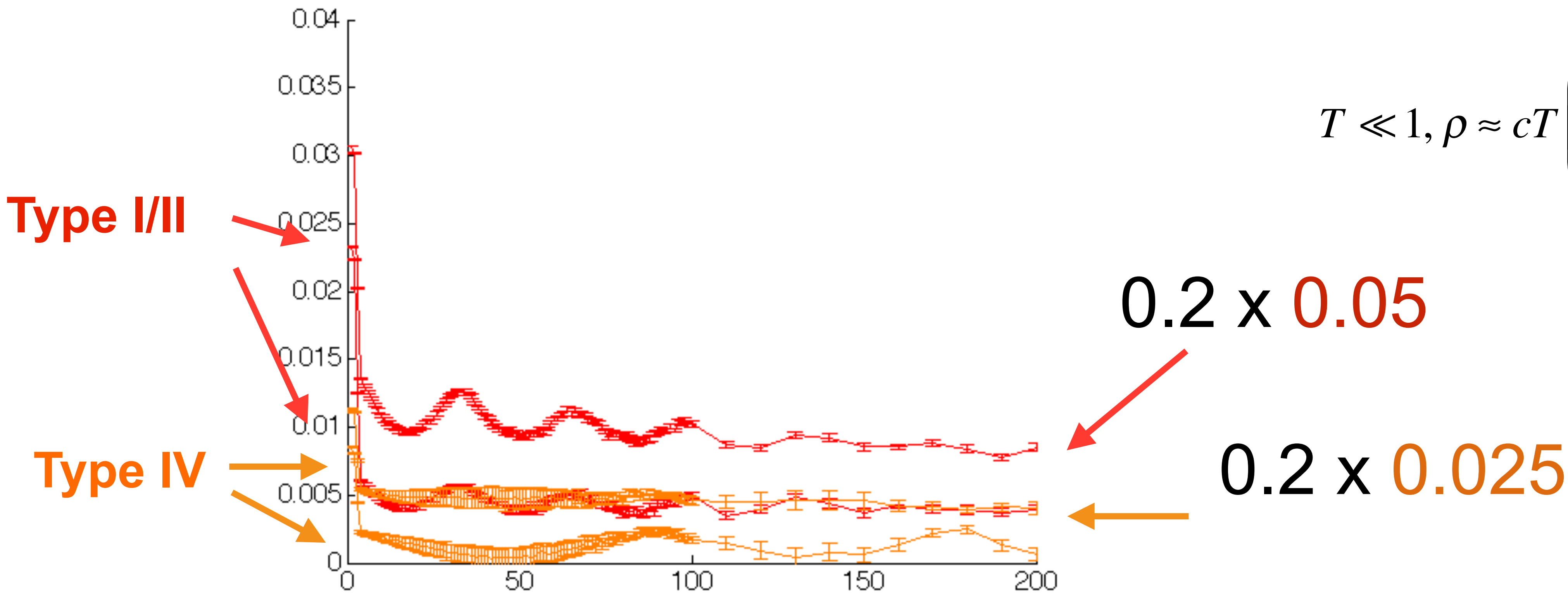

Very low correlation transfer (5%, 2.5% respectively)

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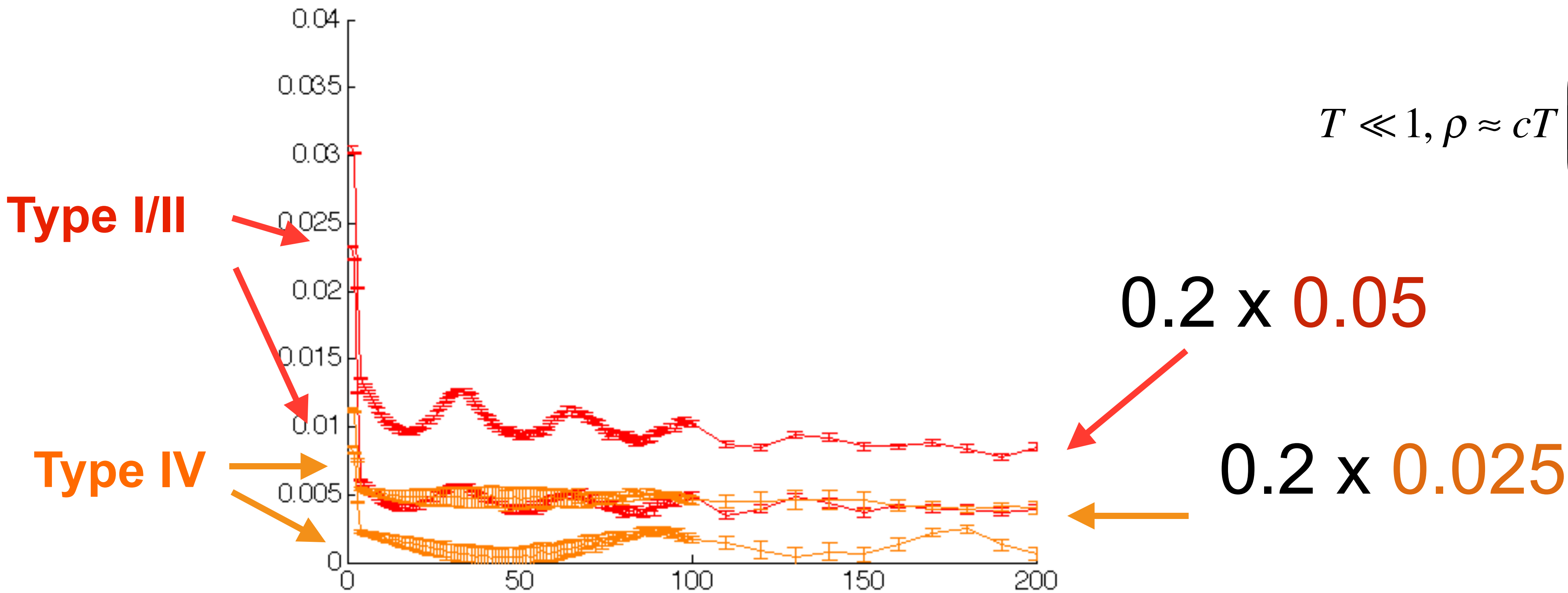
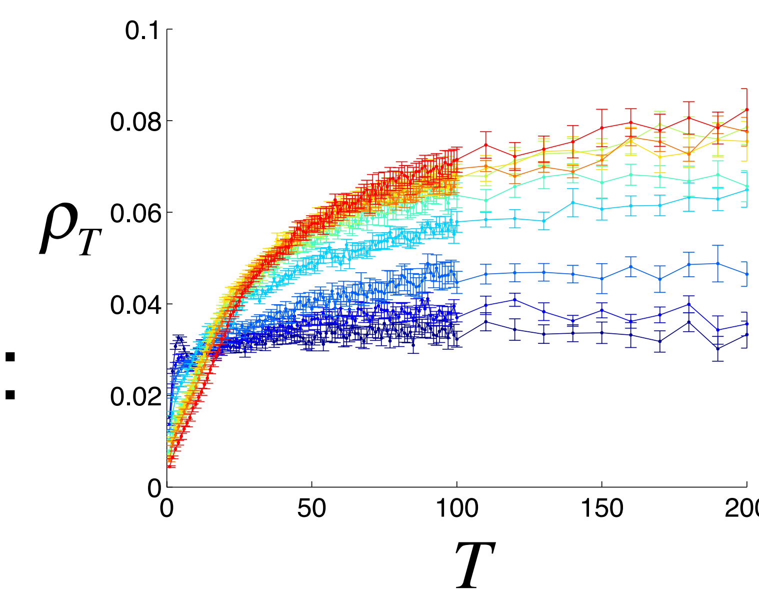
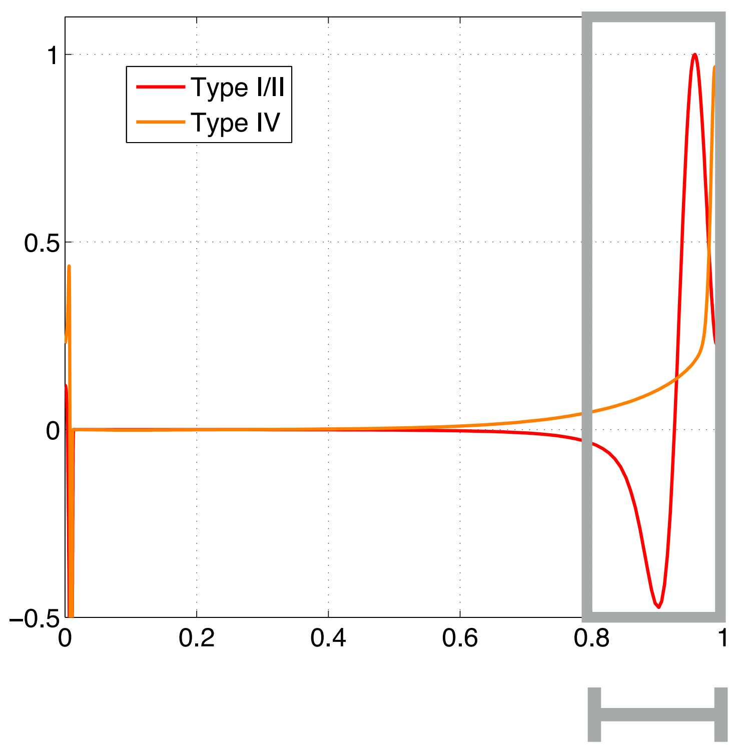


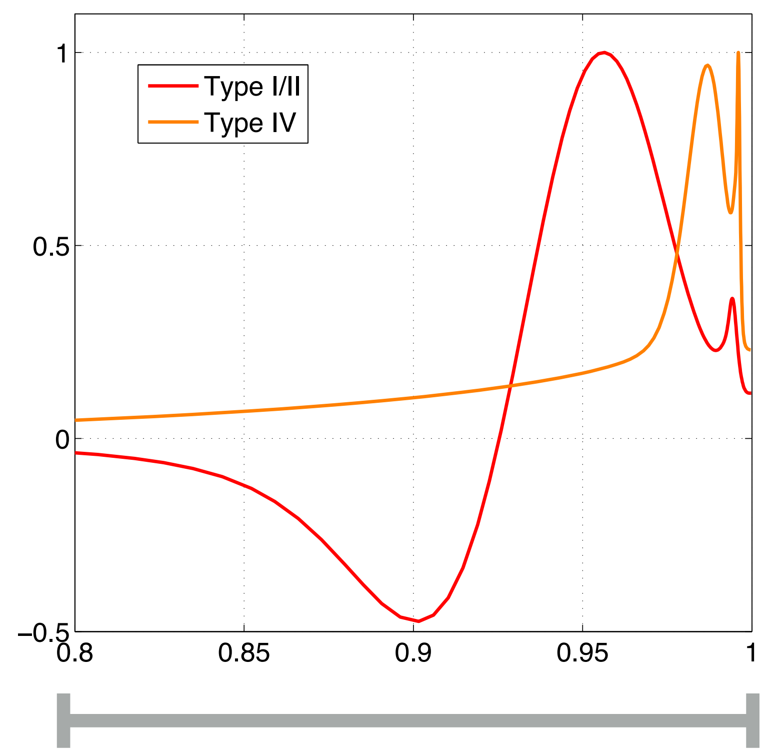
Very low correlation transfer (5%, 2.5% respectively)

(compare to CS:
40-80%)



Hypothesis: for systems with strong time scale separation, limited-support PRC => low ρ_T

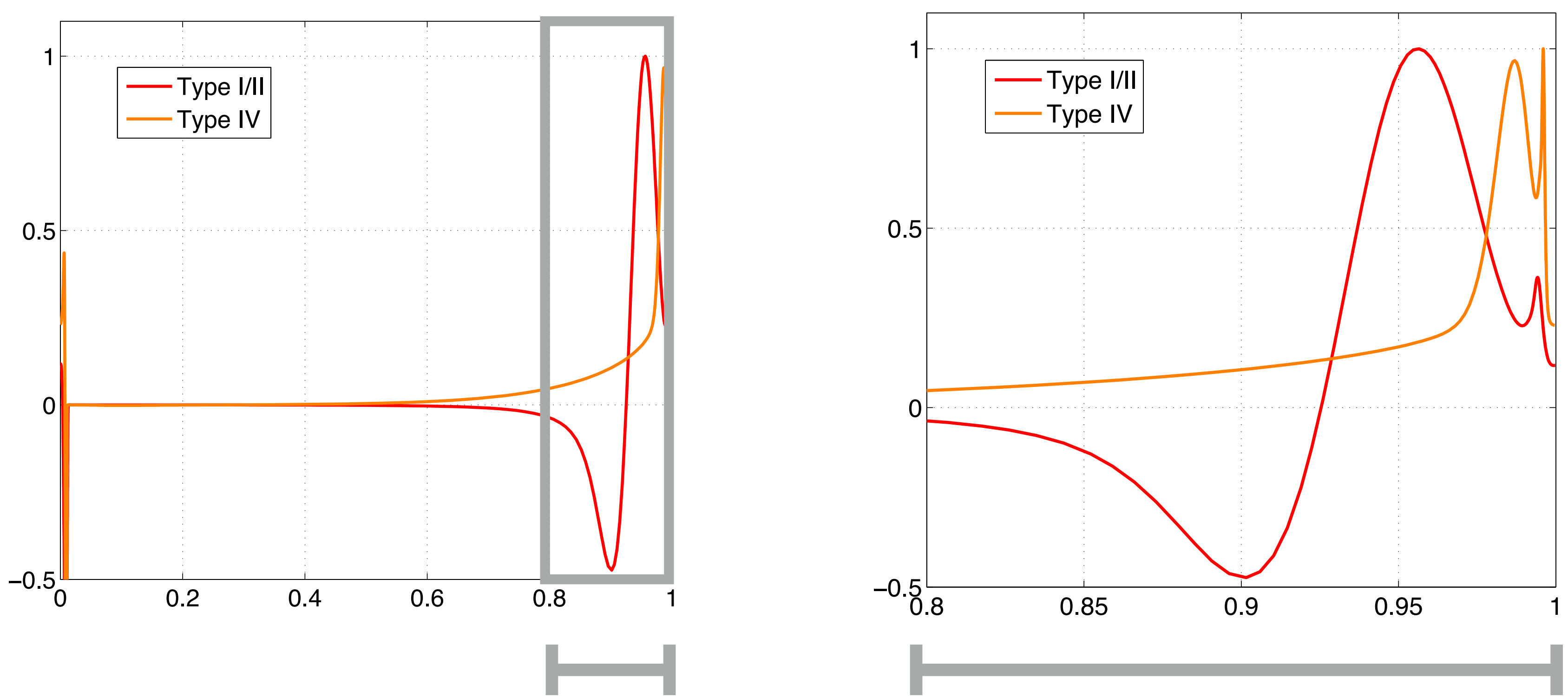




$$Z(x) = \begin{cases} \hat{Z}\left(\frac{x}{\epsilon}\right), & 0 \leq x < \epsilon \\ 0, & \epsilon < x < 1 \end{cases}$$

$$\rho_Z = c\frac{\langle Z \rangle^2}{\langle Z^2 \rangle} = c\epsilon\frac{\left\langle \hat{Z} \right\rangle^2}{\left\langle \hat{Z}^2 \right\rangle} = \epsilon\rho_{\hat{Z}}$$

Hypothesis: for systems with strong time scale separation, limited-support PRC => low ρ_T



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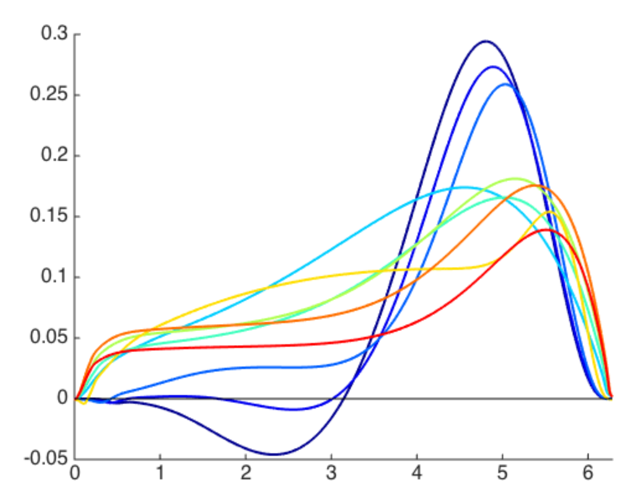
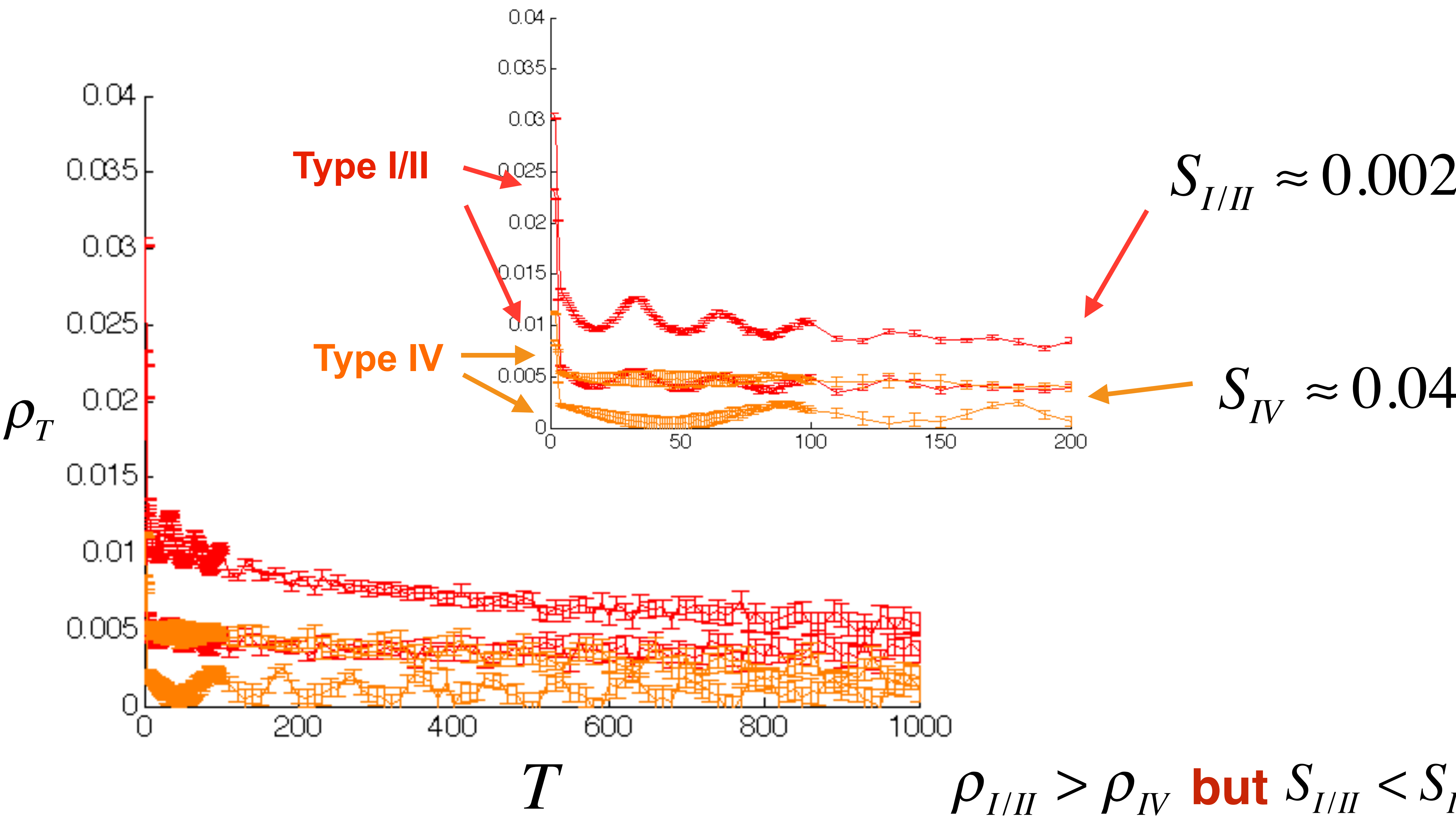
(compare w/ CS:)



Is the PRC prediction accurate?

$$T \gg 1 \rightarrow \rho_T \approx c\frac{\langle Z\rangle^2}{\langle Z^2\rangle} = cS$$

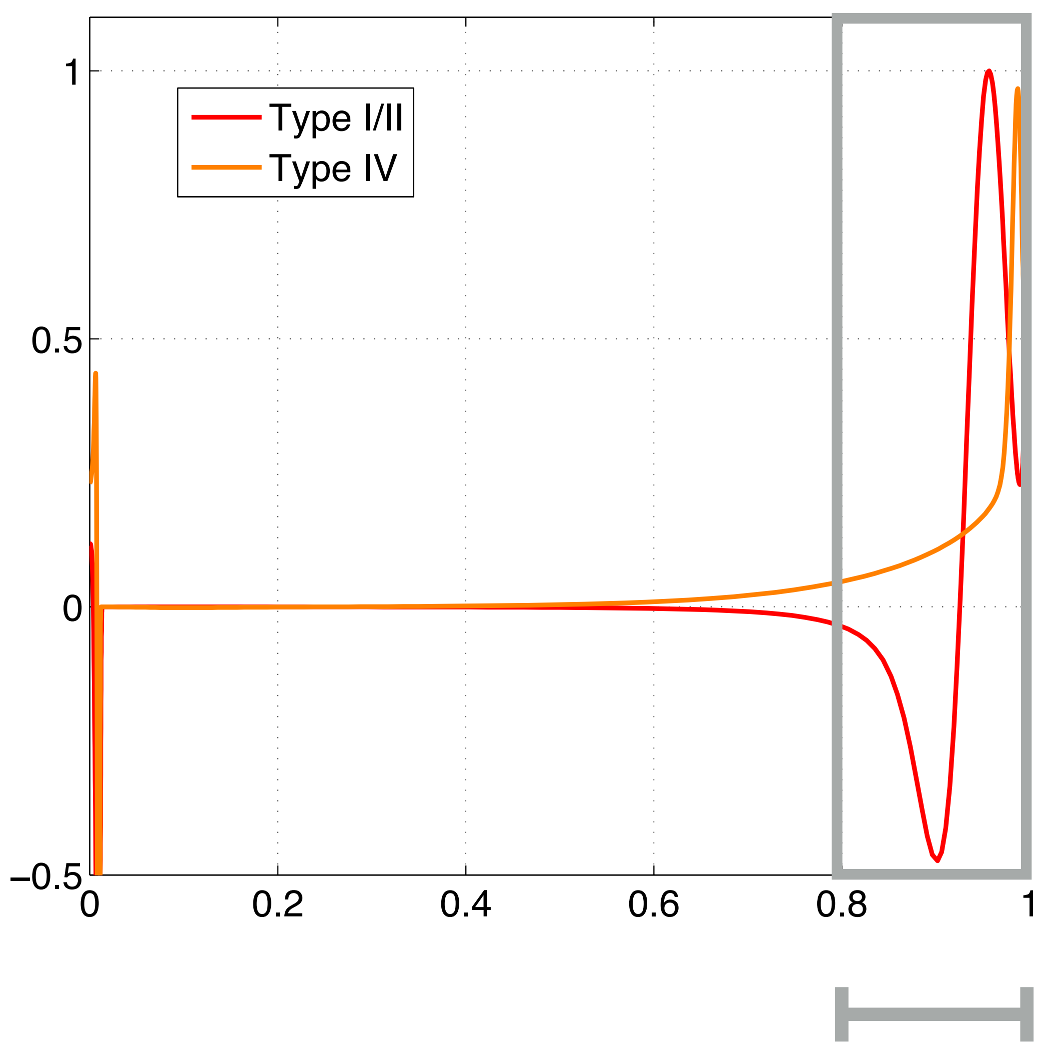
$$T \ll 1, \rho \approx cT\left(1-\frac{\langle Z\rangle^2}{\langle Z^2\rangle}\right) = cT(1-S)$$

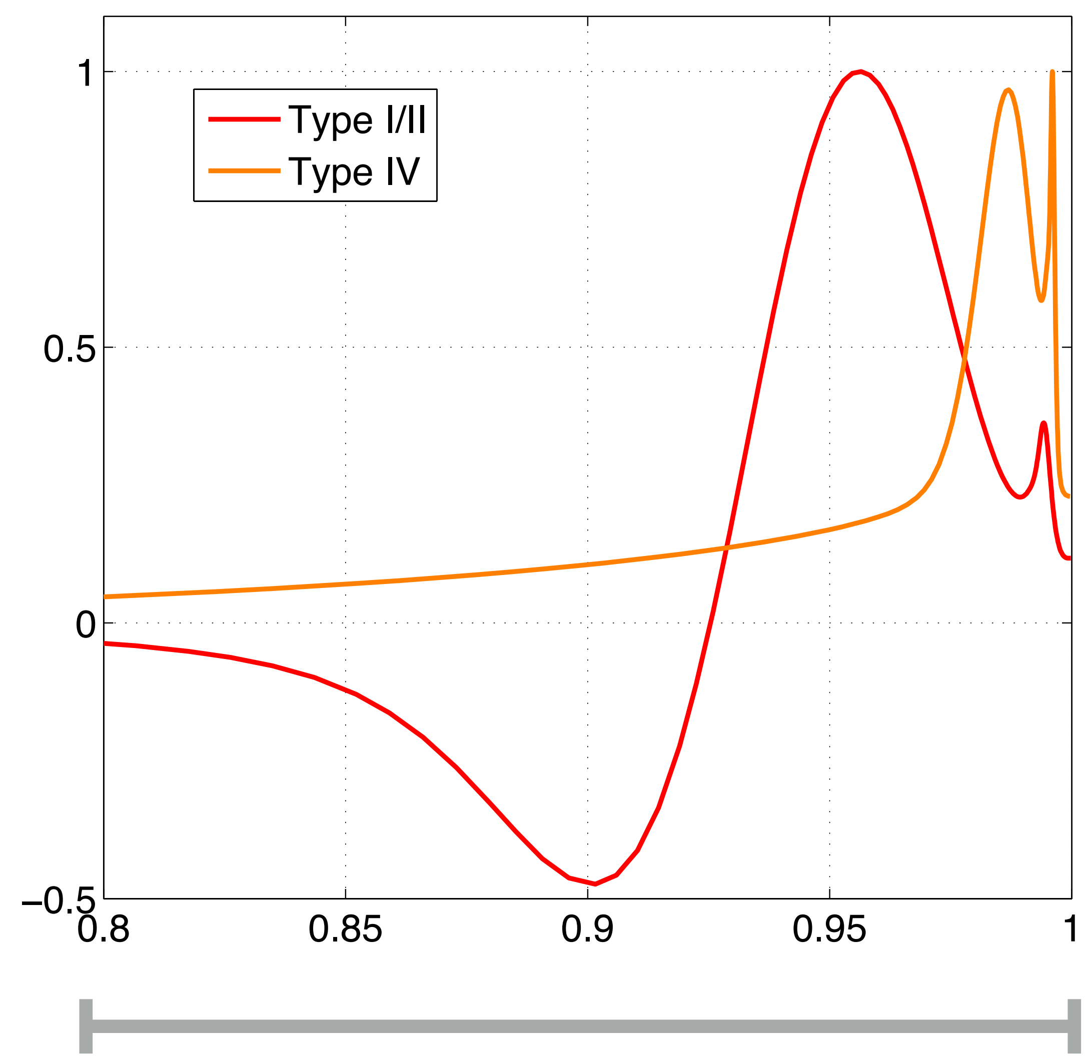


$\rho_{I/II} > \rho_{IV}$ **but** $S_{I/II} < S_{IV}$

Possible issues:

- relaxation oscillator with strong time scale separation: insensitive to noisy current except at specific times in cycle
- very hard to get long T statistics
- very hard to get *joint* statistics
- How long is long enough (for T)?





In Conclusion

• We study common input correlation transfer in both conductance-based (Connor-Stevens) and phase-oscillator models, focusing on the transition from Type I to Type II neural dynamics

• Type II neurons are more correlated at short time scales, but Type I neurons are more correlated at long time scales.

• The Type I/Type II transition can modulate downstream firing rate at biophysically relevant timescales

• Common input spike-triggered average methodology generalizes well to other excitability types (Type IV)

• PRC-based predictions less accurate: more study needed in relaxation oscillators

Funding acknowledgments:

- NSF Grant DMS-0817649, CAREER DMS-1056125
- Burroughs-Wellcome Fund
- NSF Teragrid allocation TG-IBN090004
- Mathematical Biosciences Institute (Early Career Award)