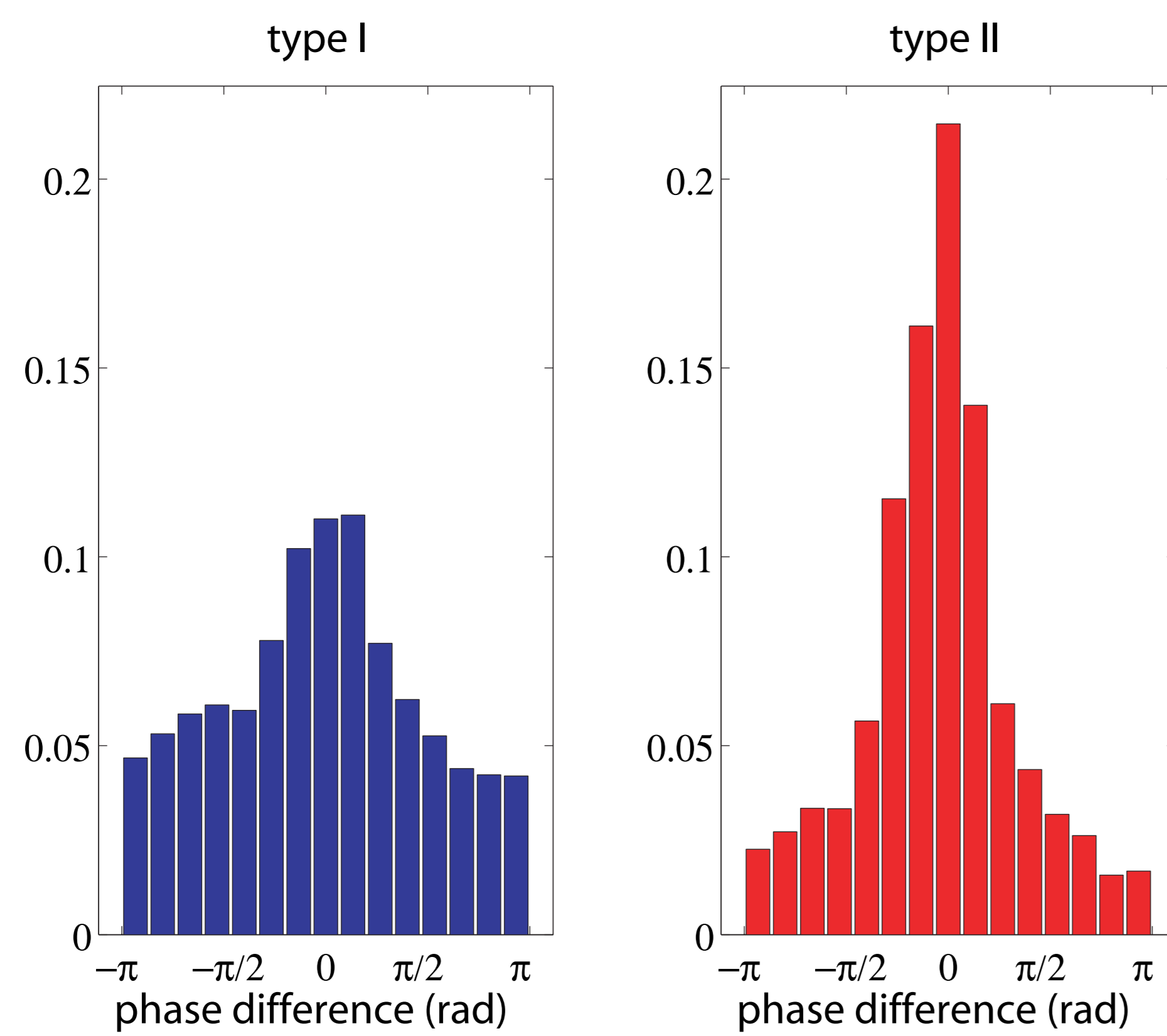


Roberto Fernández Galán^{a,b}, G. Bard Ermentrout^{b,c} and Nathaniel N. Urban^{a,b}^aCarnegie Mellon University, Dept. of Biological Sciences, ^bCenter for the Neural Basis of Cognition, ^cUniversity of Pittsburgh, Dept. of Mathematics**Abstract**

Neural reliability and stochastic synchronization are remarkable features of real neurons with important consequences for neural computation. Both phenomena are general properties of any device with a resetting threshold, as neurons are. However, certain characteristics of the single neuron dynamics can notably improve neural reliability and stochastic synchronization. In particular, *we show that, under the same conditions, neural resonators are more reliable and more susceptible to synchronize by stochastic inputs than are neural integrators.* This suggests that neurons conveying sensory information in a spike-timing code are likely to have evolved into resonators, as supported by our recent experimental studies on reliability and stochastic synchronization in the olfactory bulb.

Figure 1: Phase-lag histograms for neural pairs with prototypical phase response curves of type I (integrators) and type II neurons (resonators).

**1. Introduction**

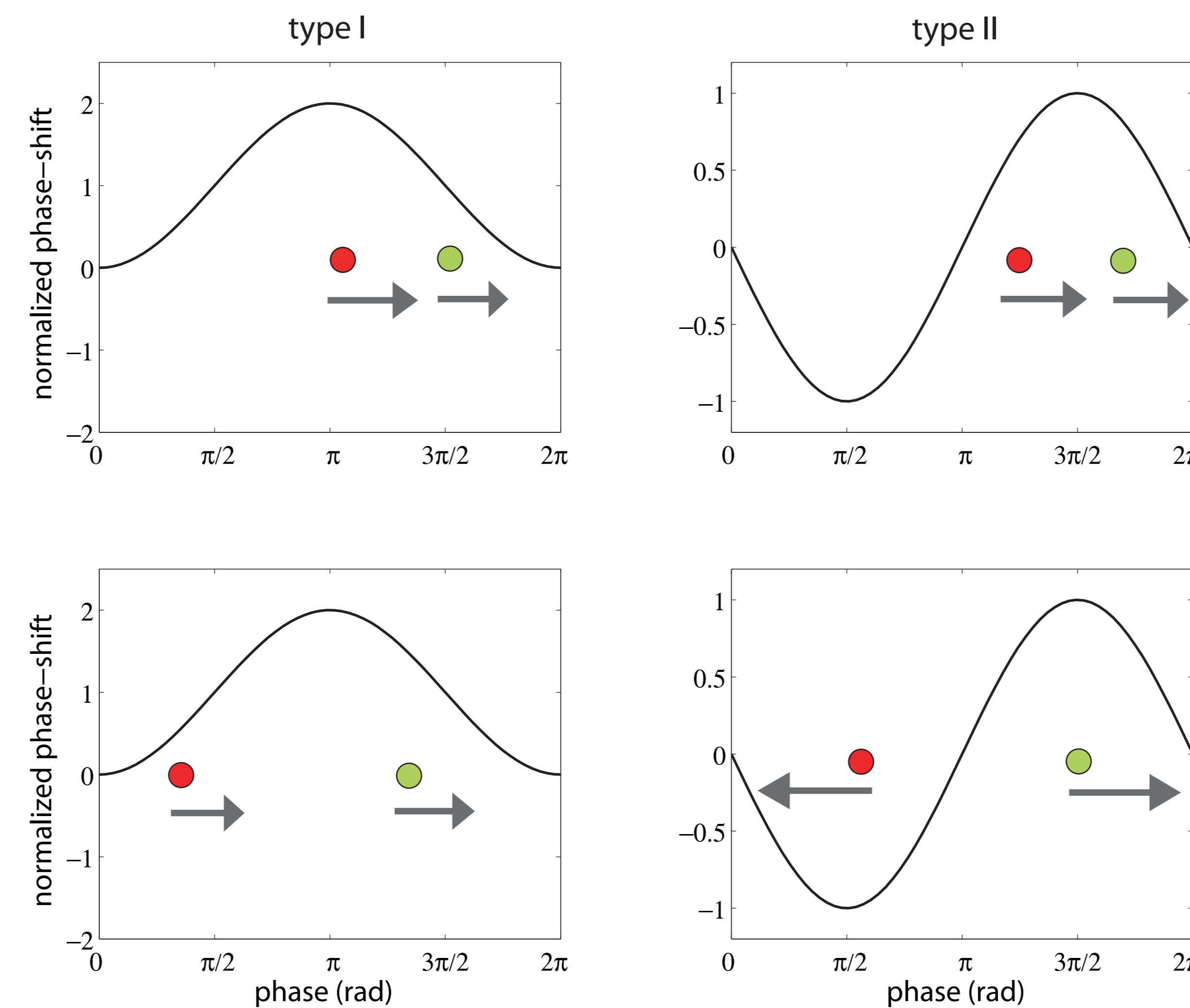
Neurons respond to several repetitions of a rapidly fluctuating stimulus in a highly reproducible manner [1,2]. This property has been referred to as neural reliability. The stochastic synchronization of an ensemble of neurons can be regarded as a generalization of this phenomenon: neurons receiving random and fast fluctuating signals that are spatially correlated will trigger correlated responses across the ensemble, which translates into synchronous action potentials [3-5]. The degree of synchronization depends on the reliability of the neurons in the ensemble and on the degree of spatial correlation of the inputs. But interestingly, stochastic synchronization occurs even when the neurons are not mutually connected [5,6].

Recently we have investigated the mechanisms for neural reliability and stochastic synchronization in experiments with acute brain slices of the olfactory bulb in rodents and also in computer simulations of simple neural models. We concluded that both phenomena are universal properties of neurons, as devices with a resetting threshold [5,6]. Here we present further computational studies on phase-oscillator models of neurons revealing that (Fig. 1) type II neural oscillators (resonators) are more reliable and more susceptible to synchronize by stochastic inputs than are type I neural oscillators (integrators). We also provide an explanation for this remarkable difference, which is based on the shape of the neuron's phase-response curve.

2. Results of simulations with phase models

Consider two neural oscillators with similar phases at a given point in time. If they receive a correlated fluctuation, they will remain close to each other in both, the resonator and the integrator case. Consider now two neural oscillators at opposite extremes of the intrinsic period. In this case, if they receive a correlated fluctuation, the phase difference of the integrators and of the resonators will evolve differently: whereas both integrators will move in the same direction, and therefore without remarkably changing their phase difference, both resonators will move in opposite directions. However, because the phase is periodic (with period 2π) moving in opposite directions actually means coming closer to each other. Thus, *correlated fluctuations will tend to diminish the phase difference between resonators no matter what their current phase is.*

Figure 2: Influence of the shape of the phase response curve on reliability and stochastic synchronization



The explanation for this phenomenon is not only valid for the simple phase responses plotted in Fig. 2 but also for phase responses obtained from conductance models (Fig. 3), like a variation of the Morris-Lecar model described in [9], which in turn closely resemble those obtained in experiments [7]. Our argument on stochastic synchronization with two oscillators holds true for the case of a large population of N non-connected neurons driven by correlated noise. To study this case for an arbitrary phase response curve, we introduce the order parameter:

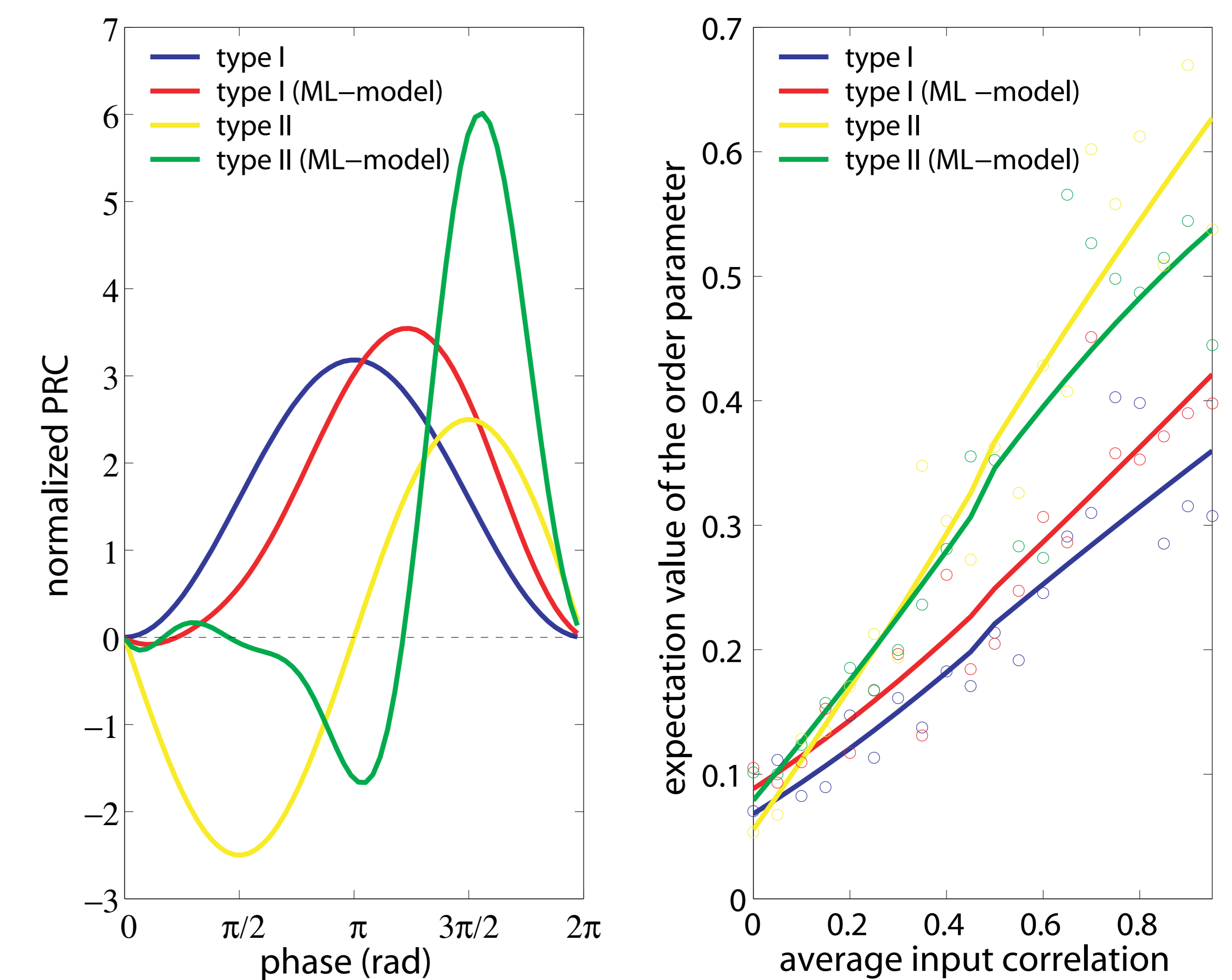
$$\Psi(t) = \left| \frac{1}{N} \sum_{n=1}^N \exp(i\phi_n(t)) \right|^2$$

3. Conclusions

Neural reliability and stochastic synchronization are remarkable features of real neurons with relevant consequences for neural computation: Whereas neural reliability is crucial for the high fidelity of sensory processing, stochastic synchronization may provide a general mechanism for binding neural representations of stimuli even across sensory modalities, and therefore for routing information in the brain.

Here we have shown that neural resonators (type II neurons) are more reliable and more susceptible to synchronize by stochastic inputs than are integrators (type I neurons). Interestingly, in recent experimental studies on the olfactory system, we have shown that mitral cells behave as neural resonators [7], which suggests that they have evolved to optimize sensory reliability and to quickly synchronize through spatially correlated barrages of inhibitory inputs from granule cells. The later mechanism may explain the emergence of oscillations in this neural network in the beta and gamma frequency bands.

Figure 3: Reliability and stochastic synchronization in networks of neurons with prototypical and realistic phase response curves



Finally, a recently published experimental study on neuronal excitability in the layer 2/3 of the somatosensory of rats has shown that regular-spiking pyramidal neurons are type I whereas fast-spiking inhibitory interneurons are type II [10]. In their paper, the authors report a remarkably higher reliability of the responses to fluctuating inputs in fast-spiking cells than in regular-spiking cells, which is in perfect agreement with the results we have presented here.

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