

cases	doc_1		doc_2		decision	id
	authors	<ul style="list-style-type: none">Konstantin BorovkovGeoffrey DecrouezMatthieu Gilson			DUPLICATES	329
	title	On stationary distributions of stochastic neural networks	authors	<ul style="list-style-type: none">K. BorovkovG. DecrouezM. Gilson		
	publication_date	2012-06-20 13:29:26+00:00	title	On Stationary Distributions of Stochastic Neural Networks		
	source	SupportedSources.ARXIV	publication_date	2012-06-20 00:00:00		
	journal	None	source	SupportedSources.SEMANTIC_SCHOLAR		
	volume		journal	Journal of Applied Probability		
	doi		volume	51		
	urls	<ul style="list-style-type: none">http://arxiv.org/pdf/1206.4489v1http://arxiv.org/abs/1206.4489v1http://arxiv.org/pdf/1206.4489v1	doi	10.1239/jap/1409932677		
	id	id3716444675054034076	urls	<ul style="list-style-type: none">https://www.semanticscholar.org/paper/ee5d913ee7fbc276a461b370db991be8dd49c2eb		
	abstract	The paper deals with non-linear Poisson neuron network models with bounded memory dynamics, that can include both Hebbian learning mechanisms and refractory periods. The state of a network is described by the times elapsed since its neurons fired within the post-synaptic transfer kernel memory span, and the current strengths of synaptic connections, the state spaces of our models being hierarchies of finite-dimensional components. We establish ergodicity of the stochastic processes describing the behaviour of the networks and prove the existence of continuously differentiable stationary distribution densities (with respect to the Lebesgue measures of corresponding dimensionality) on the components of the state space and find upper bounds for them. For the density components, we derive a system of differential equations that can be solved in a few simplest cases only. Approaches to approximate computation of the stationary density are discussed. One is to reduce the dimensionality of the problem by modifying the network so that each neuron cannot fire if the number of spikes it emitted within the post-synaptic transfer kernel memory span reaches a given threshold. We show that the stationary distribution of this 'truncated' network converges to that of the unrestricted one as the threshold increases, and that the convergence is at a super-exponential rate. A complementary approach uses discrete Markov chain approximations to the network process. We derive linear systems for the stationary distributions of these Markov chains and prove that these distributions converge weakly to the stationary laws for the original processes.	id	id9189564541793791663		
	versions		abstract	The paper deals with nonlinear Poisson neuron network models with bounded memory dynamics, which can include both Hebbian learning mechanisms and refractory periods. The state of the network is described by the times elapsed since its neurons fired within the post-synaptic transfer kernel memory span, and the current strengths of synaptic connections, the state spaces of our models being hierarchies of finite-dimensional components. We prove the ergodicity of the stochastic processes describing the behaviour of the networks, establish the existence of continuously differentiable stationary distribution densities (with respect to the Lebesgue measures of corresponding dimensionality) on the components of the state space, and find upper bounds for them. For the density components, we derive a system of differential equations that can be solved in a few simplest cases only. Approaches to approximate computation of the stationary density are discussed. One approach is to reduce the dimensionality of the problem by modifying the network so that each neuron cannot fire if the number of spikes it emitted within the post-synaptic transfer kernel memory span reaches a given threshold. We show that the stationary distribution of this "truncated" network converges to that of the unrestricted network as the threshold increases, and that the convergence is at a superexponential rate. A complementary approach uses discrete Markov chain approximations to the network process.		
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