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	authors	• M. Magill • F. Qureshi • H. W. Haan	authors	• Martin Magill • Faisal Qureshi • Hendrick W. de Haan	DUPLICATES	93
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	id	id2388043687470728638	id	id-1892612087616465622		
	abstract	We introduce a technique based on the singular vector canonical correlation analysis (SVCCA) for measuring the generality of neural network layers across a continuously-parametrized set of tasks. We illustrate this method by studying generality in neural networks trained to solve parametrized boundary value problems based on the Poisson partial differential equation. We find that the first hidden layer is general, and that deeper layers are successively more specific. Next, we validate our method against an existing technique that measures layer generality using transfer learning experiments. We find excellent agreement between the two methods, and note that our method is much faster, particularly for continuously-parametrized problems. Finally, we visualize the general representations of the first layers, and interpret them as generalized coordinates over the input domain.	abstract	We introduce a technique based on the singular vector canonical correlation analysis (SVCCA) for measuring the generality of neural network layers across a continuously-parametrized set of tasks. We illustrate this method by studying generality in neural networks trained to solve parametrized boundary value problems based on the Poisson partial differential equation. We find that the first hidden layer is general, and that deeper layers are successively more specific. Next, we validate our method against an existing technique that measures layer generality using transfer learning experiments. We find excellent agreement between the two methods, and note that our method is much faster, particularly for continuously-parametrized problems. Finally, we visualize the general representations of the first layers, and interpret them as generalized coordinates over the input domain.		
	versions		versions			