Simultaneous Dimensionality Reduction: A Possible Solution to Neuroscience's Data Complexity

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In neuroscience, we are interested in understanding the correlations between neurons firing in the brain and the resultant behaviors. Recent technological advancements allow us to record data from thousands of neurons and closely track behavioral patterns with great fidelity. It is common to use some form of dimensionality reduction to find correlations between these datasets. Often, each dataset is reduced independently, and then correlations are sought between the two reduced datasets. Alternatively, one can simultaneously reduce both datasets, keeping in each only what is relevant to the other. Previous work by others has shown that this simultaneous reduction works better on certain problems, requiring fewer samples and dimensions to achieve the same accuracy. It is not completely understood why and when these methods perform better. Through both numerical and analytical approaches, we have now confirmed that simultaneous reduction is indeed more efficient than independent reductions. Additionally, we have introduced a versatile framework for variational losses, which harnesses neural networks' capabilities in capturing nonlinear data structures. Using our framework, we developed a new method, the Deep Variational Symmetric Information Bottleneck, and demonstrated its superiority over several existing general-purpose dimensionality reduction methods. Using our adaptable framework, the method can be customized for different research problems.