AN AUTOENCODER COMPRESSION APPROACH FOR ACCELERATING LARGE-SCALE INVERSE PROBLEMS

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Partial differential equation (PDE)-constrained inverse problems are some of the most challenging and computationally demanding problems in computational science today. Fine meshes required to accurately compute the PDE solution introduce an enormous number of parameters and require large-scale computing resources such as more processors and more memory to solve such systems in a reasonable time. For inverse problems constrained by time-dependent PDEs, the adjoint method often employed to compute gradients and higher order derivatives efficiently requires solving a time-reversed, so-called adjoint PDE that depends on the forward PDE solution at each timestep. This necessitates the storage of a high-dimensional forward solution vector at every timestep. Such a procedure quickly exhausts the available memory resources. Several approaches that trade additional computation for reduced memory footprint have been proposed to mitigate the memory bottleneck, including checkpointing and compression strategies. In this work, we propose a close-to-ideal scalable compression approach using autoencoders to eliminate the need for checkpointing and substantial memory storage, thereby reducing the time-to-solution and memory requirements. We compare our approach with checkpointing and an off-the-shelf compression approach on an earth-scale ill-posed seismic inverse problem. The results verify the expected close-to-ideal speedup for the gradient and Hessian-vector product using the proposed autoencoder compression approach. To highlight the usefulness of the proposed approach, we combine the autoencoder compression with the data-informed active subspace (DIAS) prior showing how the DIAS method can be affordably extended to large-scale problems without the need for checkpointing and large memory.