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Less is More: Bigger Data from Compressive Measurements

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Compressive sensing approaches are beginning to take hold in (scanning) transmission electron microscopy (S/TEM) [1,2,3]. Compressive sensing is a mathematical theory about acquiring signals in a compressed form (measurements) and the probability of recovering the original signal by solving an inverse problem [4]. The inverse problem is underdetermined (more unknowns than measurements), so it is not obvious that recovery is possible. Compression is achieved by taking inner products of the signal with measurement weight vectors. Both Gaussian random weights and Bernoulli (0,1) random weights form a large class of measurement vectors for which recovery is possible. The measurements can also be designed through an optimization process. The key insight for electron microscopists is that compressive sensing can be used to increase acquisition speed and reduce dose.

Building on work initially developed for optical cameras, this new paradigm will allow electron microscopists to solve more problems in the engineering and life sciences. We will be collecting orders of magnitude more data than previously possible. The reason that we will have more data is because we will have increased temporal/spatial/spectral sampling rates, and we will be able to interrogate larger classes of samples that were previously too beam sensitive to survive the experiment. For example consider an *in-situ* experiment that takes 1 minute. With traditional sensing, we might collect 5 images per second for a total of 300 images. With compressive sensing, each of those 300 images can be expanded into 10 more images, making the collection rate 50 images per second, and the decompressed data a total of 3000 images [3].

But, what are the implications, in terms of data, for this new methodology? Acquisition of compressed data will require downstream reconstruction to be useful. The reconstructed data will be much larger than traditional data, we will need space to store the reconstructions during analysis, and the computational demands for analysis will be higher. Moreover, there will be time costs associated with reconstruction.

Deep learning [5] is an approach to address these problems. Deep learning is a hierarchical approach to find useful (for a particular task) representations of data. Each layer of the hierarchy is intended to represent higher levels of abstraction. For example, a deep model of faces might have sinusoids, edges and gradients in the first layer; eyes, noses, and mouths in the second layer, and faces in the third layer. There has been significant effort recently in deep learning algorithms for tasks beyond image classification such as compressive reconstruction [6] and image segmentation [7]. A drawback of deep learning, however, is that training the model requires large datasets and dedicated computational resources (to reduce training time to a few days). A second issue is that deep learning is not user-friendly and the meaning behind the results is usually not interpretable. We have shown it is possible to reduce the data set size while maintaining model quality [8] and developed interpretable models for image classification [9], but the demands are still significant.

The key to addressing these problems is to NOT reconstruct the data. Instead, we should design computational sensors that give answers to specific problems. A simple version of this idea is compressive classification [10], where the goal is to classify signal type from a small number of compressed measurements. Classification is a much simpler problem than reconstruction, so 1) much fewer measurements will be necessary, and 2) these measurements will probably not be useful for reconstruction. Other simple examples of computational sensing include determining object volume or the number of objects present in the field of view [11].

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