Machine Learning vs. Compressive Signal Processing

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This supplement provides more details about the different perspectives of machine learning and compressive signal processing approaches.

Machine learning: Machine learning (ML) often features linear models of the form

$$y = \Phi x + n,$$

where y is data that we want to predict, the Φ matrix contains different variables used for attempting to predict y, x are weights in a linear model used to predict y, and n is the unmodeled part of the problem.

Compressive signal processing: Compressive signal processing, and compressed sensing (CS) in particular, is mainly a signal acquisition approach. The unknown x is a signal, Φ is a matrix relating linear terms used in measuring x, y are our measurements, and n is noise.

Discussion: In CS, we have more flexibility than in ML. Oftentimes the analog signal acquisition system in CS allows significant flexibility in using various matrices. It could be that all possible matrices are allowed, or maybe a wide range of possible Φ. In any case, the goal is to design a matrix Φ compatible to the sensing hardware, and a recovery algorithm such that the end-to-end system provides solid estimation of x.

In ML, Φ is given, and training data for y is also available. (After training, we will apply the weights x to predict future data.) Although in principle we can identify more possible factors to predict y (these factors would be new columns in the matrix), the point of view is closer to that of a scientific problem where "nature" sets up the prediction problem, and the matrix Φ could be arbitrary. Therefore, there could be matrices and recovery algorithms that work very well in CS, but these approaches may not be suitable for ML. Information theoretic insights may help us design good (Φ, algorithm) pairs, but the same recovery algorithms may fail in ML where Φ is given to us, and may be quite different in structure from the matrices that the algorithm was designed for.