In this talk we’ll look at how large-scale, nonconvex optimization problems can be solved efficiently using a variable splitting approach. We’ll apply these methods to the decomposition of a matrix $D$ of high-dimensional data into a sum $D = L + S$, where $L$ is of low rank and $S$ is sparse. This gives us both a robust, low-dimensional model for our data, and a set of possibly large discrepancies from that model, which can contain interesting features. There are close analogies with the field of sparse signal reconstruction (known as compressive sensing), and as in that field, we find that a nonconvex optimization problem is able to give us a more useful decomposition.

To solve our nonconvex problems efficiently, we construct a new objective function, a sort of proximal analog of the $\ell^p$ quasi-norm, where $p < 1$. Our function is designed to make the minimization process computationally very efficient, with the algorithm also being parallelizable. Our featured example will be the decomposition of video. We’ll see that $L$ will be the stationary background, and $S$ will contain only the moving objects, a result that is useful for surveillance applications, and that is interesting in that it arises from purely geometric modeling. (Received September 21, 2011)