

Bachelor-/Masterthesis

Low-Rank Matrix Approximation with Sparse Learning Theory

The problem of estimating an unknown low-rank matrix from noisy measurements has been a long-standing problem in various fields, such as system identification, signal processing, data-driven prediction, model order reduction, and recommendation algorithms. Classical solutions to this problem involve shrinking the singular values of the matrix. However, this may not be possible when the low-rank constraint is embedded in a larger problem.

This project leverages the relation between low-rank approximation (LRA) and sparse learning. Sparse learning investigates methods to enforce sparsity constraints in optimization problems. By considering singular value decomposition, the LRA problem can be recast as a sparse learning problem with infinitely many rank-1 basis matrices. Existing algorithms in sparse learning can then be applied to solve the LRA problem. Possible research topics include 1) investigating equivalence/similarities between LRA and infinite-dimensional sparse learning algorithms, 2) applying advanced sparse learning algorithms to the LRA problem, and 3) developing tractable constraints on basis matrices to enforce structural requirements.

Prospective students should be familiar with optimization and its numerical implementation in Matlab or Python. A strong mathematical background in linear algebra and knowledge of sparse learning/compressive sensing and system identification would be a plus.

$$\begin{matrix}
 \begin{matrix} \square & \square & \square & \square \\ \square & \square & \square & \square \\ \square & \square & \square & \square \\ \square & \square & \square & \square \end{matrix} & = & \begin{matrix} \square & \square & \square & \square \\ \square & \square & \square & \square \\ \square & \square & \square & \square \\ \square & \square & \square & \square \end{matrix} & \begin{matrix} \square & \square & \square & \square \\ \square & \square & \square & \square \\ \square & \square & \square & \square \\ \square & \square & \square & \square \end{matrix} & \begin{matrix} \square & \square & \square & \square \\ \square & \square & \square & \square \\ \square & \square & \square & \square \\ \square & \square & \square & \square \end{matrix} \\
 \mathbf{M} & = & \mathbf{U} & \mathbf{\Sigma} & \mathbf{V}^* \\
 m \times n & & m \times m & m \times n & n \times n
 \end{matrix}$$

$$\begin{matrix}
 \begin{matrix} \square & \square & \square & \square \\ \square & \square & \square & \square \\ \square & \square & \square & \square \\ \square & \square & \square & \square \end{matrix} & \begin{matrix} \square & \square & \square & \square \\ \square & \square & \square & \square \\ \square & \square & \square & \square \\ \square & \square & \square & \square \end{matrix} & = & \begin{matrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{matrix} \\
 \mathbf{U} & \mathbf{U}^* & = & \mathbf{I}_m
 \end{matrix}$$

$$\begin{matrix}
 \begin{matrix} \square & \square & \square & \square \\ \square & \square & \square & \square \\ \square & \square & \square & \square \\ \square & \square & \square & \square \end{matrix} & \begin{matrix} \square & \square & \square & \square \\ \square & \square & \square & \square \\ \square & \square & \square & \square \\ \square & \square & \square & \square \end{matrix} & = & \begin{matrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{matrix} \\
 \mathbf{V} & \mathbf{V}^* & = & \mathbf{I}_n
 \end{matrix}$$

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