

Guaranteed Rank Minimization via Singular Value Projections

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Affine Constrained Rank Minimization Problem (ARMP)

$$\begin{aligned} \text{(ARMP)} : \quad & \min_X \text{rank}(X) \\ & \text{s.t. } \mathcal{A}(X) = b. \end{aligned}$$

$$X \in \mathbb{R}^{m \times n}, \mathcal{A} : \mathbb{R}^{m \times n} \rightarrow \mathbb{R}^d, b \in \mathbb{R}^d.$$

- $d \ll mn$ (typically, $d = 6nk$)
- Applications:
 - Matrix completion: Netflix Challenge
 - Linear time-invariant systems
 - Embedding using missing Euclidean distances
- NP-hard even to approximate within log factor (Meka et al.'08)

Singular Value Projection (SVP)

$$\begin{aligned} (\mathbf{RARMP}) : \min_X \psi(X) &= \frac{1}{2} \|\mathcal{A}(X) - b\|_2^2, \\ \text{s.t } X &\in \mathcal{C}(k) = \{X : \text{rank}(X) \leq k\}. \end{aligned}$$

- SVP: Adapt classical projected gradient
- Efficient projection onto non-convex rank constraint using **SVD**
- Converges to the optimal solution under **certain RIP conditions**
- SVP-Newton: Second order adaptation of SVP

Results

- Singular Value Projection (SVP) algorithm
 - Simple analysis for ARMP (with RIP)
 - Partial progress for matrix completion
 - Simple Newton-step based extension: SVP-Newton and SVP-NewtonD
- Experimental Results:
 - Synthetic Datasets with uniform sampling
 - Synthetic Datasets with noise and more realistic power-law sampling
 - MovieLens Dataset
- SVP much faster and more stable than existing methods
- For more details: Poster No. **W56**

Code available at: <http://www.cs.utexas.edu/users/pjain/svp/>