Guaranteed Rank Minimization via Singular Value Projections

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Affine Constrained Rank Minimization Problem (ARMP)

$$(\textbf{ARMP}): \quad \min_{X} \ rank(X) \quad \text{s.t} \ \mathcal{A}(X) = b.$$

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

- $d \ll mn$ (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)

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

- 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
  - Synethtic 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/