

Generic analysis of local convergence



Cong Ma

University of Chicago, Autumn 2021

Outline

- Low-rank matrix sensing
- Phase retrieval
- Low-rank matrix completion

Low-rank matrix sensing

- Groundtruth: rank- r matrix $\mathbf{M}^\star \in \mathbb{R}^{n_1 \times n_2}$
- Observations:

$$y_i = \langle \mathbf{A}_i, \mathbf{M}^\star \rangle, \quad \text{for } 1 \leq i \leq m$$

- Goal: recover \mathbf{M}^\star based on linear measurements $\{\mathbf{A}_i, y_i\}_{1 \leq i \leq m}$

How many measurements are needed

- $m \geq n_1 n_2$ “generic” measurements suffice given theory of solving linear equations
- But \mathbf{M}^* only has $O((n_1 + n_2)r)$ degrees of freedom. Ideally, one hope for using only $O((n_1 + n_2)r)$ measurements

Recovery is possible if $\{A_i\}$'s satisfy restricted isometry property

Restricted isometry property (RIP)

Define linear operator $\mathcal{A} : \mathbb{R}^{n_1 \times n_2} \mapsto \mathbb{R}^m$ to be

$$\mathcal{A}(\mathbf{M}) = [m^{-1/2} \langle \mathbf{A}_i, \mathbf{M} \rangle]_{1 \leq i \leq m}$$

Definition 8.1

The operator \mathcal{A} is said to satisfy r -RIP with RIP constant $\delta_r < 1$ if

$$(1 - \delta_r) \|\mathbf{M}\|_F^2 \leq \|\mathcal{A}(\mathbf{M})\|_2^2 \leq (1 + \delta_r) \|\mathbf{M}\|_F^2$$

holds simultaneously for all \mathbf{M} of rank at most r .

- Many random designs satisfy RIP with high probability
- For instance, when \mathbf{A}_i is composed of i.i.d. $\mathcal{N}(0, 1)$ entries, \mathcal{A} obeys r -RIP with constant δ_r as soon as $m \gtrsim (n_1 + n_2)r/\delta_r^2$

An optimization-based method

Consider the simple case when M^* is psd and rank 1, i.e.,

$$M^* = x^* x^{*\top}$$

Then least-squares estimation yields

$$\underset{x \in \mathbb{R}^n}{\text{minimize}} \quad f(x) = \frac{1}{4m} \sum_{i=1}^m \left(\langle A_i, x x^\top \rangle - y_i \right)^2$$

Gradient descent

Starting from \mathbf{x}^0 , one proceeds by

$$\begin{aligned}\mathbf{x}^{t+1} &= \mathbf{x}^t - \eta \nabla f(\mathbf{x}^t) \\ &= \mathbf{x}^t - \frac{\eta}{m} \sum_{i=1}^m \left(\langle \mathbf{A}_i, \mathbf{x}^t \mathbf{x}^{t\top} \rangle - y_i \right) \mathbf{A}_i \mathbf{x}^t\end{aligned}$$

Here we made simplifying assumption that \mathbf{A}_i is symmetric

- Under random design, when $m \rightarrow \infty$, this mirrors PCA problem with loss $\frac{1}{4} \|\mathbf{x} \mathbf{x}^\top - \mathbf{x}^* \mathbf{x}^{*\top}\|_{\text{F}}^2$; GD works locally
- How about finite-sample case?

RIP helps

Local convergence of gradient descent

Theorem 8.2

Suppose that \mathcal{A} obeys 4-RIP with constant $\delta_4 \leq 1/44$. If $\|\mathbf{x}^0 - \mathbf{x}^\|_2 \leq \|\mathbf{x}^*\|_2/12$, then GD with $\eta = 1/(3\|\mathbf{x}^*\|_2^2)$ obeys*

$$\|\mathbf{x}^t - \mathbf{x}^*\|_2 \leq \left(\frac{11}{12}\right)^t \|\mathbf{x}^0 - \mathbf{x}^*\|_2, \quad \text{for } t = 0, 1, 2, \dots$$

- local linear convergence within basin of attraction $\{\mathbf{x} \mid \|\mathbf{x} - \mathbf{x}^*\|_2 \leq \|\mathbf{x}^*\|_2/12\}$

Proof of Theorem 8.2

In view of theory of gradient descent for locally strongly convex and smooth functions, it suffices to prove that

$$0.25\|\mathbf{x}^\star\|_2^2\mathbf{I}_n \preceq \nabla^2 f(\mathbf{x}) \preceq 3\|\mathbf{x}^\star\|_2^2\mathbf{I}_n$$

holds for all

$$\{\mathbf{x} \mid \|\mathbf{x} - \mathbf{x}^\star\|_2 \leq \|\mathbf{x}^\star\|_2/12\}$$

To analyzing spectral properties of $\nabla^2 f(\mathbf{x})$, we focus on quadratic forms

$$\mathbf{z}^\top \nabla^2 f(\mathbf{x}) \mathbf{z}$$

Proof of Theorem 8.2 (cont.)

Simple calculations show

$$\mathbf{z}^\top \nabla^2 f(\mathbf{x}) \mathbf{z} = \frac{1}{m} \sum_{i=1}^m \langle \mathbf{A}_i, \mathbf{x} \mathbf{x}^\top - \mathbf{x}^* \mathbf{x}^{*\top} \rangle (\mathbf{z}^\top \mathbf{A}_i \mathbf{z}) + 2(\mathbf{z}^\top \mathbf{A}_i \mathbf{x})^2,$$

which admits a more “compact” expression

$$\begin{aligned} \mathbf{z}^\top \nabla^2 f(\mathbf{x}) \mathbf{z} &= \langle \mathcal{A}(\mathbf{x} \mathbf{x}^\top - \mathbf{x}^* \mathbf{x}^{*\top}), \mathcal{A}(\mathbf{z} \mathbf{z}^\top) \rangle \\ &\quad + \frac{1}{2} \langle \mathcal{A}(\mathbf{z} \mathbf{x}^\top + \mathbf{x} \mathbf{z}^\top), \mathcal{A}(\mathbf{z} \mathbf{x}^\top + \mathbf{x} \mathbf{z}^\top) \rangle \end{aligned}$$

RIP preserves inner product

Lemma 8.3

Suppose that \mathcal{A} satisfies $2r$ -RIP with constant $\delta_{2r} < 1$, then

$$|\langle \mathcal{A}(\mathbf{X}), \mathcal{A}(\mathbf{Y}) \rangle - \langle \mathbf{X}, \mathbf{Y} \rangle| \leq \delta_{2r} \|\mathbf{X}\|_F \|\mathbf{Y}\|_F$$

Proof of Theorem 8.2 (cont.)

Apply Lemma 8.3 to obtain

$$\begin{aligned} & \left| \langle \mathcal{A}(\mathbf{x}\mathbf{x}^\top - \mathbf{x}^*\mathbf{x}^{*\top}), \mathcal{A}(\mathbf{z}\mathbf{z}^\top) \rangle - \langle \mathbf{x}\mathbf{x}^\top - \mathbf{x}^*\mathbf{x}^{*\top}, \mathbf{z}\mathbf{z}^\top \rangle \right| \\ & \leq \delta_4 \|\mathbf{x}\mathbf{x}^\top - \mathbf{x}^*\mathbf{x}^{*\top}\|_F \|\mathbf{z}\mathbf{z}^\top\|_F \leq 3\delta_4 \|\mathbf{x}^*\|_2^2 \|\mathbf{z}\|_2^2, \end{aligned}$$

while last relation uses $\|\mathbf{x} - \mathbf{x}^*\|_2 \leq \|\mathbf{x}^*\|_2$. Similarly, one has

$$\begin{aligned} & \left| \langle \mathcal{A}(\mathbf{z}\mathbf{x}^\top + \mathbf{x}\mathbf{z}^\top), \mathcal{A}(\mathbf{z}\mathbf{x}^\top + \mathbf{x}\mathbf{z}^\top) \rangle - \|\mathbf{z}\mathbf{x}^\top + \mathbf{x}\mathbf{z}^\top\|_F^2 \right| \\ & \leq \delta_4 \|\mathbf{z}\mathbf{x}^\top + \mathbf{x}\mathbf{z}^\top\|_F^2 \leq 4\delta_4 \|\mathbf{x}\|_2^2 \|\mathbf{z}\|_2^2 \leq 16\delta_4 \|\mathbf{x}\|_2^2 \|\mathbf{z}\|_2^2 \end{aligned}$$

Proof of Theorem 8.2 (cont.)

Define

$$g(\mathbf{x}, \mathbf{z}) := \langle \mathbf{x}\mathbf{x}^\top - \mathbf{x}^*\mathbf{x}^{*\top}, \mathbf{z}\mathbf{z}^\top \rangle + \frac{1}{2} \|\mathbf{z}\mathbf{x}^\top + \mathbf{x}\mathbf{z}^\top\|_F^2$$

Key conclusion so far: when $\|\mathbf{x} - \mathbf{x}^*\|_2 \leq \|\mathbf{x}^*\|_2$, $\mathbf{z}^\top \nabla^2 f(\mathbf{x}) \mathbf{z}$ is close to $g(\mathbf{x}, \mathbf{z})$

It boils down to upper and lower bounding $g(\mathbf{x}, \mathbf{z})$ —a much easier task

Spectral initialization

Construct

$$\mathbf{M} = \frac{1}{m} \sum_{i=1}^m y_i \mathbf{A}_i$$