Guarantees of Riemannian Optimization for Low Rank Matrix Completion

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Abstract

We study the Riemannian optimization methods on the embedded manifold of low rank matrices for the problem of matrix completion, which is about recovering a low rank matrix from its partial entries. Assume \( m \) entries of an \( n \times n \) rank \( r \) matrix are sampled independently and uniformly with replacement. We first prove that with high probability the Riemannian gradient descent and conjugate gradient descent algorithms initialized by one step hard thresholding are guaranteed to converge linearly to the measured matrix provided

\[
m \geq C_\kappa n^{1.5} r \log^{1.5}(n),
\]

where \( C_\kappa \) is a numerical constant depending on the condition number of the underlying matrix. The sampling complexity has been further improved to

\[
m \geq C_\kappa n r^2 \log^2(n)
\]

via the resampled Riemannian gradient descent initialization. The analysis of the new initialization procedure relies on an asymmetric restricted isometry property of the sampling operator and the curvature of the low rank matrix manifold. Numerical simulation shows that the algorithms are able to recover a low rank matrix from nearly the minimum number of measurements.

Keywords. Matrix completion, Riemannian optimization, low rank matrix manifold, tangent space, gradient descent and conjugate gradient descent methods

Mathematics Subject Classification. 15A29, 41A29, 65F10, 68Q25, 15A83, 53B21, 90C26, 65K05

1 Introduction

The problem of matrix completion attempts to recover a low rank matrix from a subset of sampled entries. This problem arises from a wide variety of practical context, such as model reduction [33], pattern recognition [18], and machine learning [4, 5]. Since the data matrix is assumed to be low rank, it is natural to seek the lowest rank matrix consistent with the observed entries by solving a rank minimization problem

\[
\min_{Z \in \mathbb{R}^{n \times n}} \text{rank}(Z) \text{ subject to } P_\Omega(Z) = P_\Omega(X),
\]

\[\tag{1}\]

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where $X \in \mathbb{R}^{n \times n}$ is the underlying matrix to be reconstructed, $\Omega$ is a subset of indices for the known entries, and $P_\Omega$ is the associated sampling operator which acquires only the entries indexed by $\Omega$. Here we restrict our discussion to square matrices for ease of exposition, but emphasize that all the results can be extended straightforwardly to the case where the measured matrix is rectangular.

Problem (1) is generally NP-hard [24] and computationally intractable. In a seminal paper of Candès and Recht [13], the authors studied nuclear norm minimization for matrix completion, where the rank objective in (1) is replaced by the nuclear norm of matrices which is the sum of the singular values. It was observed in the same paper that we cannot expect to recover all the low rank matrices from their partial known entries. For example, if there exists only one nonzero entry in a matrix, we need to see almost all of its entries to infer that it is not a zero matrix. This observation motivates the following assumption.

A0 ([13]). Let $X \in \mathbb{R}^{n \times n}$ be a rank $r$ matrix with the reduced singular value decomposition (SVD) $X = U\Sigma V^*$. We assume $X$ is $\mu_0$-incoherent; that is, there exists an absolute numerical constant $\mu_0 > 0$ such that

$$\|P_U (e_i)\| \leq \sqrt{\frac{\mu_0 r}{n}} \quad \text{and} \quad \|P_V (e_j)\| \leq \sqrt{\frac{\mu_0 r}{n}}$$

for $1 \leq i, j \leq n$. Here $e_\ell \ (\ell = i, j)$ is the $\ell$-th canonical basis of $\mathbb{R}^n$, and $P_U$ and $P_V$ are the orthogonal projections onto the column and row spaces of $X$ respectively.

A matrix is $\mu_0$-incoherent implies that its singular vectors are weakly correlated with the canonical basis. In addition, (2) is equivalent to $\|U^{(i)}\| \leq \sqrt{\frac{\mu_0 r}{n}}$ and $\|V^{(j)}\| \leq \sqrt{\frac{\mu_0 r}{n}}$, where $U^{(i)}$ and $V^{(j)}$ are the $i$-th and $j$-th rows of $U$ and $V$ respectively. We also require that the measured matrix cannot be too spiky.

A1 ([29]). Let $X \in \mathbb{R}^{n \times n}$ be a rank $r$ matrix. We assume that exists another absolute numerical constant $\mu_1$ such that

$$\|X\|_\infty \leq \mu_1 \sqrt{\frac{r}{n^2} \|X\|}.$$  

This manuscript investigates recovery guarantees of a class of Riemannian gradient descent and conjugate gradient algorithms for matrix completion under the sampling with replacement model. We first establish the local convergence of the Riemannian gradient descent algorithm and a restarted variant of the Riemannian conjugate gradient descent algorithm. Then we prove that $O(nr^2 \log^2(n))$ number of measurements are sufficient for the Riemannian optimization algorithms to converge linearly to the underlying low rank matrix when the algorithms are properly initialized.

1.1 Notations and Organization of the Manuscript

The rest of the manuscript is organized as follows. We first summarize the notations used throughout this manuscript in the remainder of this section. In Sec. 2 we present the Riemannian gradient descent and conjugate gradient descent algorithms based on the embedded manifold of low rank matrices from the perspective of iterative hard thresholding algorithms. Then we present the theoretical guarantees of the algorithms. Empirical observations in Sec. 3 demonstrates the efficiency and robustness of the Riemannian optimization algorithms. The proofs of the main results are
presented in Sec. 4 and Sec. 5 concludes this manuscript with potential future directions. Finally, the Appendix provides proofs for the supporting technical lemmas.

Throughout this manuscript, we denote matrices by uppercase letters and vectors by lowercase letters. In particular, $X$ denotes the $n \times n$ rank $r$ matrix to be reconstructed, with $\sigma_{\min}(X)$ and $\sigma_{\max}(X)$ being its smallest nonzero and largest singular values respectively. The condition number of $X$ is denoted by $\kappa$, which is defined as $\kappa = \frac{\sigma_{\max}(X)}{\sigma_{\min}(X)}$. We always assume that $X$ obeys the conditions set out in A0 and A1. For any matrix $Z$, the spectral norm of $Z$ is denoted by $\|Z\|$, the Frobenius norm is denoted by $\|Z\|_F$, and the maximum magnitude of its entries is denoted by $\|Z\|_\infty$. We use $Z^{(i)}$ to represent the $i$-th row of $Z$. The Euclidean norm of a vector $x$ is denoted by $\|x\|$. Operators that map matrices to matrices are denoted by calligraphic letters. In particular, $\mathcal{I}$ denotes the identity operator. The spectral norm of a linear operator $\mathcal{A}$ is denoted by $\|\mathcal{A}\|$.

Given a collection of indices $\Omega$ with $|\Omega| = m$ (counting multiplicity) for the observed entries, we define $p = \frac{m}{n^2}$ which is the probability of each entry being observed, and $\mathcal{P}_\Omega$ represents the sampling operator that maps a matrix to its component-wise product with the matrix $\sum_{(i,j) \in \Omega} e_i e_j^\top$. In the main results, $\varepsilon_0$ is a positive numerical constant which controls the size of the contraction neighborhood of an algorithm and its value only depends on the algorithm. Finally, we use $C$ to denote an absolute numerical constant whose value may change according to context.

## 2 Algorithms and Main Results

We consider the sampling with replacement model for $\Omega$ in which each index is sampled independently from the uniform distribution on $\{1, \cdots , n\} \times \{1, \cdots , n\}$. This model can be viewed as a proxy for the uniform sampling model and the failure probability under the uniform sampling model is less than or equal to the failure probability under the sampling with replacement model [38]. Though there may exist duplicates in $\Omega$, the maximum number of duplication can be upper bounded with high probability.

**Lemma 2.1** [38]. With probability at least $1 - n^{2 - 2\beta}$, the maximum number of repetitions of any entry in $\Omega$ is less than $\frac{\beta}{3}\beta \log(n)$ for $n \geq 9$ and $\beta > 1$.

It follows immediately from Lem. 2.1 that with high probability we have $\|\mathcal{P}_\Omega\| \leq \frac{\beta}{3}\beta \log(n)$.

Many computationally efficient algorithms have been designed to target the matrix completion problem directly by considering the following non-convex formulation\(^1\)

$$\min_{Z \in \mathbb{R}^{n \times n}} \frac{1}{2} \langle Z - X, \mathcal{P}_\Omega (Z - X) \rangle \text{ subject to rank}(Z) = r, \quad (4)$$

see [7, 25, 30, 43, 23, 50, 44, 47, 36, 34, 35, 26, 8] and references therein for an incomplete review. Normalized iterative hard thresholding [43] (NIHT, also known as SVP [25] or IHT [21] when the stepsize is fixed) is a projected gradient descent algorithm which updates the estimate along the gradient descent direction of the objective function in (4), followed by the projection onto the set of rank $r$ matrices via the hard thresholding operator:

$$X_{l+1} = \mathcal{H}_r (X_l + \alpha_l \mathcal{P}_\Omega (X - X_l)), \quad (5)$$

\(^1\)Note that the objective function in (4) is the same as $\frac{1}{2} \sum_{(i,j) \in \Omega} (Z_{ij} - X_{ij})^2$, but it might not be equal to $\frac{1}{2} \|\mathcal{P}_\Omega (Z - X)\|_F^2$ because in general $\mathcal{P}_\Omega$ is not a projection (i.e., $\mathcal{P}_\Omega^2 \neq \mathcal{P}_\Omega$) when $\Omega$ is sampled with replacement.
Algorithm 1: Riemannian Gradient Descent (RGrad)

| Initialization: $X_0 = U_0 \Sigma_0 V_0^*$ |
|------------------------------------------------|
| for $l = 0, 1, \cdots$ do |
| 1. $G_l = P_\Omega (X - X_l)$ |
| 2. $\alpha_l = \frac{\| P_{T_l}(G_l) \|_2^2}{\langle P_{T_l}(G_l), P_{\Omega} P_{T_l}(G_l) \rangle}$ |
| 3. $W_l = X_l + \alpha_l P_{T_l}(G_l)$ |
| 4. $X_{l+1} = H_r(W_l)$ |
| end for |

where the hard thresholding operator $H_r$ first computes the SVD of a matrix and then sets all but the $r$ largest singular values to zero

$$H_r(Z) := PA_rQ^* \quad \text{where} \quad Z = PAQ^* \text{ is the SVD of } Z, \text{ and } A_r(i, i) := \begin{cases} \Lambda(i, i) & i \leq r \\ 0 & i > r. \end{cases} \quad (6)$$

NIHT suffers from the slow asymptotic convergence rate of first order methods as a gradient descent algorithm. To overcome this slow convergence rate of NIHT, a conjugate gradient iterative hard thresholding (CGIHT) algorithm has been developed in [7]. In each iteration of CGIHT, the new search direction is computed as a weighted sum of the gradient descent direction and the past search direction, and the selection of the weights guarantees that the new search direction is conjugate orthogonal to the past search direction when projected onto the column space of the current estimate. In both NIHT and CGIHT, we need to compute the largest $r$ singular values and their associated singular vectors of an $n \times n$ matrix in each iteration. Although Krylov subspace methods can be applied to compute this truncated SVD, it is still computationally expensive especially when $n$ is large and $r$ is moderate. The Riemannian optimization algorithms based on the embedded manifold of rank $r$ matrices can reduce the computational cost of the truncated SVD dramatically by exploring the local structure of low rank matrices.

We first present the Riemannian gradient descent method for matrix completion in Alg. 1. Let $X_l = U_l \Sigma_l V_l^*$ be the current estimate and $T_l$ be the tangent space of the rank $r$ matrix manifold at $X_l$; that is,

$$T_l = \{ U_l Z_1^* + Z_2 V_l^* : Z_1, Z_2 \in \mathbb{R}^{n \times r} \}.$$  

The new estimate $X_{l+1}$ is obtained by updating $X_l$ along $P_{T_l}(G_l)$, the gradient descent direction projected onto the tangent space $T_l$, using the steepest stepsize $\alpha_l$, and then followed by hard thresholding the estimate back onto the set of rank $r$ matrices.

In the Riemannian conjugate gradient descent method (Alg. 2), the search direction is a linear combination of the projected gradient descent direction and the past search direction projected onto the tangent space of the current estimate. The orthogonalization weight $\beta_l$ in Alg. 2 is selected in a way such that $P_{T_l}(P_l)$ is conjugate orthogonal to $P_{T_l}(P_{l-1})$, which follows from CGIHT in [7]. It is worth noting that there are other selections for $\beta_l$ following from the non-linear conjugate gradient descent method in convex optimization [47]. In particular, the Riemannian conjugate gradient descent algorithm (LRGeomCG) developed in [47] for matrix completion uses the Polak-Ribière+ selection for $\beta_l$. In this manuscript, we interpret the Riemannian optimization methods directly as iterative hard thresholding algorithms with subspace projections. For the differential geometry ideas behind the algorithms, we refer the readers to [1].
Theorem 2.2 (Local Convergence of Riemannian Gradient Descent)
For the Riemannian gradient descent algorithm (Alg. 1), we have the following theorem.

Given initial guess in this neighborhood, Algs. 1 and 2 will converge linearly to the true solution.

We first identify a small neighborhood around the measured low rank matrix such that for any two QR factorizations of $n \times r$ matrices and one full SVD of a $2r \times 2r$ matrix as matrices in $T_l$ are at most rank $2r$. To see this, notice that $W_l$ in Algs. 1 and 2 can be rewritten as

$$W_l = X_l + \mathcal{P}_{T_l}(Z_l),$$

where $Z_l = \alpha_l G_l$ in Alg. 1 and $Z_l = \alpha_l(G_l + \beta_l P_{l-1})$ in Alg. 2. So

$$W_l = U_l \Sigma_l V_l^* + U_l U_l^* Z_l + Z_l V_l V_l^* - U_l U_l^* Z_l V_l^*$$
$$= U_l (\Sigma_l + U_l^* Z_l V_l) V_l^* + U_l U_l^* (I - V_l V_l^*) (I - U_l U_l^*) Z_l V_l V_l^*$$
$$= U_l (\Sigma_l + U_l^* Z_l V_l) V_l^* + U_l Y_l V_l^* + Y_l^* V_l^*.$$

Let $Y_1 = Q_1 R_1$, $Y_2 = Q_2 R_2$ be the QR factorizations of $Y_1$ and $Y_2$ respectively. Then $U_l^* Q_2 = 0$ and $V_l^* Q_1 = 0$, and we have

$$W_l = \begin{bmatrix} U_l & Q_2 \end{bmatrix} \begin{bmatrix} \Sigma_l + U_l^* Z_l V_l & R_1^* \\ R_2 & 0 \end{bmatrix} \begin{bmatrix} V_l^* \\ Q_1^* \end{bmatrix}$$
$$:= \begin{bmatrix} U_l & Q_2 \end{bmatrix} M_l \begin{bmatrix} V_l^* \\ Q_1^* \end{bmatrix}.$$

Since $\begin{bmatrix} U_l & Q_2 \end{bmatrix}$ and $\begin{bmatrix} V_l & Q_1 \end{bmatrix}$ are both unitary matrices, the SVD of $W_l$ can be obtained from the SVD of $M_l$, which is a $2r \times 2r$ matrix.

2.1 Local Convergence

We first identify a small neighborhood around the measured low rank matrix such that for any given initial guess in this neighborhood, Algs. 1 and 2 will converge linearly to the true solution. For the Riemannian gradient descent algorithm (Alg. 1), we have the following theorem.

**Theorem 2.2** (Local Convergence of Riemannian Gradient Descent). Let $X \in \mathbb{R}^{n \times n}$ be the measured rank $r$ matrix and $T$ be the tangent space of the rank $r$ matrix manifold at $X$. Suppose

$$\|\mathcal{P}_\Omega\| \leq \frac{8}{3} \beta \log(n), \quad (7)$$

Algorithm 2: Riemannian Conjugate Gradient Descent (RCG)

**Initialization**: $X_0 = U_0 \Sigma_0 V_0^*$, $\beta_0 = 0$ and $P_{-1} = 0$

for $l = 0, 1, \ldots$

1. $G_l = \mathcal{P}_\Omega (X - X_l)$
2. $\beta_l = \frac{\langle \mathcal{P}_{T_l}(G_l) \rangle}{\langle \mathcal{P}_{T_l}(P_{l-1}) \rangle}$
3. $P_l = \mathcal{P}_{T_l}(G_l) + \beta_l \mathcal{P}_{T_l}(P_{l-1})$
4. $\alpha_l = \frac{\langle \mathcal{P}_{T_l}(P_l) \rangle}{\langle \mathcal{P}_{T_l}(P_{l-1}) \rangle}$
5. $W_l = X_l + \alpha_l P_l$
6. $X_{l+1} = \mathcal{H}_r(W_l)$

end for
\[ \| \mathcal{P}_T - p^{-1} \mathcal{P}_T \mathcal{P}_\Omega \mathcal{P}_T \| \leq \varepsilon_0, \quad (8) \]
\[ \frac{\| X_0 - X \|_F}{\sigma_{\min}(X)} \leq \frac{3p^{1/2}\varepsilon_0}{16\beta \log(n)(1 + \varepsilon_0)}, \quad (9) \]

where \( \beta > 1 \), and \( \varepsilon_0 \) is a positive numerical constant such that

\[ \nu_g = \frac{18\varepsilon_0}{1 - 4\varepsilon_0} < 1. \quad (10) \]

Then the iterates \( X_l \) generated by Alg. 1 satisfy

\[ \| X_l - X \|_F \leq \nu_g^l \| X_0 - X \|_F. \]

To state a similar result for the Riemannian conjugate gradient descent algorithm, we introduce a restarted variant of Alg. 2; that is, \( \beta_l \) is set 0 and restarting occurs as long as either of the following conditions is violated

\[ \frac{| \langle \mathcal{P}_T l(G_l), \mathcal{P}_T l(P_{l-1}) \rangle \rangle |}{\| \mathcal{P}_T l(G_l) \|_F \| \mathcal{P}_T l(P_{l-1}) \|_F} \leq \kappa_1, \quad \| \mathcal{P}_T l(G_l) \|_F \leq \kappa_2 \| \mathcal{P}_T l(P_{l-1}) \|_F. \quad (11) \]

The restarting conditions are introduced not only for the sake of proof, but also to improve the robustness of the non-linear conjugate gradient descent methods [37]. The first restarting condition guarantees that the residual will be substantially orthogonal to the past search direction when projected onto the tangent space of current estimate so that the new search direction can be sufficiently gradient related. In the classical CG algorithm for linear systems, the residual is exactly orthogonal to all the past search directions. Roughly speaking, the second restarting condition implies that the projection of current residual cannot be too large when compared to the projection of the past residual since the search direction is gradient related by the first restarting condition. In our implementations, we take \( \kappa_1 = 0.1 \) and \( \kappa_2 = 1. \)

**Theorem 2.3** (Local Convergence of restarted Riemannian Conjugate Gradient Descent). Let \( X \in \mathbb{R}^{n \times n} \) be the measured rank \( r \) matrix and \( T \) be the tangent space of the rank \( r \) matrix manifold at \( X \). Suppose

\[ \| \mathcal{P}_\Omega \| \leq \frac{8}{3} \beta \log(n), \quad (12) \]
\[ \| \mathcal{P}_T - p^{-1} \mathcal{P}_T \mathcal{P}_\Omega \mathcal{P}_T \| \leq \varepsilon_0, \quad (13) \]
\[ \frac{\| X_0 - X \|_F}{\sigma_{\min}(X)} \leq \frac{3p^{1/2}\varepsilon_0}{16\beta \log(n)(1 + \varepsilon_0)}, \quad (14) \]

where \( \beta > 1 \), and \( \varepsilon_0 \) is a positive numerical constant. Assume that \( \varepsilon_0 \) obeys

\[ \tau_1 + \tau_2 < 1, \quad (15) \]

where

\[ \tau_1 = \frac{18\varepsilon_0 - 10\kappa_1 \varepsilon_0(1 + 4\varepsilon_0)}{(1 - 4\varepsilon_0) - \kappa_1 (1 + 4\varepsilon_0)} + \frac{4\kappa_2 \varepsilon_0 + \kappa_1 \kappa_2}{1 - 4\varepsilon_0}, \quad \tau_2 = \frac{8\kappa_2 \varepsilon_0 + 2\kappa_1 \kappa_2}{1 - 4\varepsilon_0}. \]
Then we have \( \nu_{cg} = \frac{1}{2} \left( \tau_1 + \sqrt{\tau_1^2 + 4\tau_2} \right) < 1 \) and the iterates \( X_i \) generated by Alg. 2 subject to the restarting conditions in (11) satisfy

\[
\|X_i - X\|_F \leq \nu_{cg}^i \|X_0 - X\|_F.
\]

When \( \kappa_1 = \kappa_2 = 0 \), (15) is reduced to (10). On the other hand we have

\[
\lim_{\varepsilon_0 \to 0} (\tau_1 + \tau_2) = 3\kappa_1\kappa_2.
\]

So if \( \kappa_1\kappa_2 < 1/3 \), \( \tau_1 + \tau_2 \) can be less than one when \( \varepsilon_0 \) is small. In particular, when \( \kappa_1 = 0.1 \) and \( \kappa_2 = 1 \), a sufficient condition for \( \tau_1 + \tau_2 < 1 \) is \( \varepsilon_0 \leq 0.01 \).

The proofs of Thms. 2.2 and 2.3 are presented in Secs. 4.2 and 4.3 respectively.

### 2.2 Initialization and Recovery Guarantees

In Thms. 2.2 and 2.3, we list three conditions to guarantee the convergence of the algorithms. The requirement for \( \mathcal{P}_\Omega \) to be bounded in (7) and (12) is just an artifact of the sampling model, and it can be satisfied with probability at least \( 1 - n^2/2\beta \) following from Lem. 2.1. The second condition (8) and (13) is a local restricted isometry property which has been established in [13] for the Bernoulli model and in [22, 38] for the sampling with replacement model, and it also plays a key role in nuclear norm minimization for matrix completion. For the sampling with replacement model, Thm. A.2 implies that as long as

\[
m \geq C\beta \left( \frac{\mu_0}{\varepsilon_0^2} \right) nr \log(n),
\]

\[
\left\| \mathcal{P}_T - p^{-1} \mathcal{P}_T \mathcal{P}_\Omega \mathcal{P}_T \right\| \leq \varepsilon_0 \text{ with probability at least } 1 - 2n^2/2\beta.
\]

Thus the only issue that remains to be addressed is how to produce an initial guess that is sufficiently close to the measured matrix. We will consider two initialization strategies.

#### 2.2.1 Initialization via One Step Hard Thresholding

A widely used initialization for matrix completion is to set \( X_0 = H_r \left( p^{-1} \mathcal{P}_\Omega(X) \right) \). The approximation error \( \|X_0 - X\|_F \) can be estimated as follows.

**Lemma 2.4.** Suppose \( \Omega \) with \( |\Omega| = m \) is a set of indices sampled independently and uniformly with replacement. Let \( X_0 = H_r \left( p^{-1} \mathcal{P}_\Omega(X) \right) \). Then for all \( \beta > 1 \)

\[
\|X_0 - X\|_F \leq \sqrt{\frac{64\beta \mu_0^2 nr^2 \log(n)}{3m}} \|X\|
\]

with probability at least \( 1 - 2n^{1-\beta} \) provided \( m \geq 6\beta n \log(n) \).

The proof of Lem. 2.4 is presented in Sec. 4.4 which follows from a direct application of Thm. A.3 for the sampling with replacement model. A similar inequality has been established in [29] for \( \hat{X}_0 = H_r \left( p^{-1} \mathcal{P}_\Omega(X) \right) \) under the Bernoulli model using random graph theory, where \( \mathcal{P}_\Omega(X) \) is a trimmed matrix obtained by setting all the rows and columns of \( \mathcal{P}_\Omega(X) \) with too many observed
Algorithm 3 Initialization via Resampled Riemannian Gradient Descent and Trimming

Partition $\Omega$ into $L + 1$ equal groups: $\Omega_0, \cdots, \Omega_L$; and the size of each group is denoted by $\hat{m}$.

Set $Z_0 = \mathcal{H}_r\left(\frac{\hat{m}}{n}P_{\Omega_0}(X)\right)$.

for $l = 0, \cdots, L - 1$ do
1. $\hat{Z}_l = \text{trim}(Z_l)$
2. $Z_{l+1} = \mathcal{H}_r\left(\hat{Z}_l + \frac{n^2}{m}P_{\Omega_l} P_{\Omega_{l+1}} (X - \hat{Z}_l)\right)$
end for

Output: $X_0 = Z_L$

Algorithm 4 trim

Input: $Z_l = U_l \Sigma_l V_l^*$

Output: $\hat{Z}_l = A_l \Sigma_l B_l^*$, where $A_l^{(i)} = \frac{U_l^{(i)}}{\|U_l^{(i)}\|} \min\left(\|U_l^{(i)}\|, \sqrt{\frac{\mu_0 r}{n}}\right)$, $B_l^{(i)} = \frac{V_l^{(i)}}{\|V_l^{(i)}\|} \min\left(\|V_l^{(i)}\|, \sqrt{\frac{\mu_0 r}{n}}\right)$

entries to zero. Moreover, an application of the standard Chernoff bound can further show that with high probability there are no rows or columns of $P_{\Omega_l}(X)$ with too many entries \([27]\).

It follows from Lem. 2.4 that the third condition (9) and (14) in Thms. 2.2 and 2.3 can be satisfied with probability at least $1 - 2n^{1-\beta}$ if

$$m \geq C\beta^{3/2}\left(\frac{\mu_1(1 + \varepsilon_0)}{\varepsilon_0}\right)^{\frac{1}{3/2}} n^{3/2} r \log^{3/2}(n).$$

Therefore we can establish the following theorem.

**Theorem 2.5** (Recovery Guarantee I). Let $X \in \mathbb{R}^{n \times n}$ be the measured rank $r$ matrix. Suppose $\Omega$ with $|\Omega| = m$ is a set of indices sampled independently and uniformly with replacement. Let $X_0 = \mathcal{H}_r\left(p^{-1}P_{\Omega}(X)\right)$. Then for all $\beta > 1$, the iterates of the Riemannian gradient descent algorithm (Alg. 1) and the restarted Riemannian conjugate gradient algorithm (Alg. 2, restarting when either the inequality in (11) is violated) with $\kappa_1 \kappa_2 < 1/3$ is guaranteed to converge to $X$ with probability at least $1 - 3n^3 - 2\beta - 2n^{1-\beta}$ provided

$$m \geq C\beta^{3/2} \max\left\{\frac{\mu_0}{\varepsilon_0}, \frac{\mu_1(1 + \varepsilon_0)}{\varepsilon_0}\right\} n^{3/2} r \log^{3/2}(n).$$

2.2.2 Initialization via Resampled Riemannian Gradient Descent and Trimming

The sampling complexity in Thm. 2.5 depends on $n^{1.5}$, rather than linearly on $n$. To attenuate this dependence, we consider a more delicate initialization scheme via the resampled Riemannian gradient descent followed by trimming in each iteration, see Alg. 3. The trimming procedure (Alg. 4) projects the estimate onto the set of $\mu_0$-incoherent matrices, while the resampling scheme breaks the dependence between the past iterate and the new sampling set. So we can establish the required isometry properties which are needed to prove the linear convergence of the iterates until
they reach an order of $p^{1/2}$ neighborhood around the measured matrix where Thms. 2.2 and 2.3 are activated. Since the main computational cost in each iteration of Alg. 3 is $O(|\Omega_l| r)$ flops [7], the total computational cost of Alg. 3 is only slightly larger than one iteration of Alg. 1 applied on the full sampling set $\Omega$. The output of Alg. 3 satisfies the following property.

**Lemma 2.6.** Let $X \in \mathbb{R}^{n \times n}$ be the measured rank $r$ matrix. Then for all $\beta > 1$, with probability at least $1 - 2n^{1-\beta} - 4L^2n^{2-2\beta}$,

$$\|X_0 - X\|_F \leq \left(\frac{5}{6}\right)^L \sigma_{\min}(X) \frac{L}{256\kappa^2}$$

provided $\hat{m} \geq C\beta \max\{\mu_0, \mu_1^2\} \kappa^6nr^2 \log(n)$.

The proof of Lem. 2.6 is presented in Sec. 4.5. In Alg. 3, we use fixed stepsize $\frac{n^2}{\hat{m}}$ for ease of exposition, which can be replaced by the adaptive stepsize similar to Alg. 1. Lemma 2.6 implies that if we take

$$L \geq 6 \log \left(\frac{\beta n \log(n)}{24\epsilon_0}\right),$$

the third condition (11) and (14) in Thms. 2.2 and 2.3 can be satisfied with probability at least $1 - 2n^{1-\beta} - 24 \log \left(\frac{\beta n \log(n)}{24\epsilon_0}\right)n^{2-2\beta}$. So together with Lem. 2.1, Thms. A, 2.2 and 2.3 we can establish the following theorem.

**Theorem 2.7** (Recovery Guarantee II). Let $X \in \mathbb{R}^{n \times n}$ be the measured rank $r$ matrix. Suppose $\Omega$ with $|\Omega| = m$ is a set of indices sampled independently and uniformly with replacement. Let $X_0$ be the output of Alg. 3. Then for all $\beta > 1$, the iterates of the Riemannian gradient descent algorithm (Alg. 1) and the restarted Riemannian conjugate gradient algorithm (Alg. 3, restarting when either the inequality in (11) is violated) with $\kappa_1 \kappa_2 < 1/3$ is guaranteed to converge to $X$ with probability at least $1 - 2n^{1-\beta} - \left(24\log \left(\frac{\beta n \log(n)}{24\epsilon_0}\right) + 3\right)n^{2-2\beta}$ provided

$$m \geq C\beta \max\{\mu_0, \mu_1^2\} \kappa^6nr^2 \log(n) \log \left(\frac{\beta n \log(n)}{24\epsilon_0}\right).$$

### 2.3 Related Work

From the pioneer work of Recht, Fazel, and Parrilo [39, 19] and Candès and Recht [13], the low rank matrix reconstruction problem has received intensive investigations from both the theoretical and algorithmic aspects. Recht, Fazel, and Parrilo [39] studied nuclear norm minimization for the low rank matrix recovery problem where each measurement is obtained by taking inner product between the underlying low rank matrix and a dense measurement matrix. They showed that if the restricted isometry constant of the sensing operator is smaller than a numerical constant, then nuclear norm minimization is guaranteed to recover a low rank matrix exactly. Moreover, this condition can be satisfies for certain family of random measurement matrices provided the number of measurements is $O(nr)$ [12]. Many non-convex optimization algorithms have also been studied for low rank matrix recovery based on either the restricted isometry constant of the sensing operator or directly on the random measurement models, see [30, 31, 43, 25, 45, 17, 53, 40, 6, 52, 51] and
references therein. In particular, the Riemannian gradient descent and conjugate gradient descent algorithms for low rank matrix recovery have been studied in [49].

Candès and Recht [13] first studied matrix completion by nuclear norm minimization under the Bernoulli model and incoherent conditions, showing that $O(n^{1.2}r \log(n))$ measurements are sufficient for successful recovery with high probability. This result was subsequently sharpened to $O(nr \log^{\alpha}(n))$ in [22, 38, 14, 15]. The nuclear norm minimization problem can be solved by either semidefinite programming [46] or iterative soft thresholding algorithms [9]. A gradient descent algorithm on the Grassmannian manifold of low dimensional subspaces was studied in [29]. It was shown that $O(\kappa^6nr^2)$ number of measurements allows for convergence of the algorithm, which was established by penalizing the incoherence of the estimate in the loss function. The proof in [29] relies on the stationary point analysis and linear convergence rate of the algorithm was not shown. This framework was further extended in [42] to gradient descent algorithms based on the product factorization of low rank matrices. Alternating minimization was studied in [28, 27] with the best known sampling complexity being $O(\kappa^8nr \log(\frac{n}{\epsilon}))$, where the desired accuracy $\epsilon$ was introduced because the algorithm requires a fresh set of measurements in each iteration. In contrast, Thm. 2.7 only requires resampling for the initialization stage and our algorithms can converge linearly to the desired low rank matrix (within arbitrary precision) for the fixed number of measurements.

3 Numerical Experiments

In this section, we present empirical observations of the Riemannian gradient descent and conjugate gradient descent algorithms for random tests. We test three algorithms, namely, the Riemannian gradient descent algorithm (Alg. 1), the Riemannian conjugate gradient descent algorithm (Alg. 2), and the Riemannian conjugate gradient algorithm being restarted if one of the conditions in (11) is violated. These three algorithms are abbreviated as RGrad, RCG, and RCG restarted respectively. For RCG restarted, we take $\kappa_1 = 0.1$ and $\kappa_2 = 1$ in (11). All tested algorithms are initialized by one step hard thresholding instead of Alg. 3 as the former has already led to very good performance (see Figs. 12 and 13) and preliminary numerical results didn’t find much difference between these two initialization strategies for random simulations. The numerical experiments are conducted on a Mac Pro laptop with 2.5GHz quad-core Intel Core i7 CPUs and 16 GB memory and executed from Matlab 2014b.

3.1 Empirical Phase Transition

An important question in matrix completion is how many of measurements are needed in order for an algorithm to be able to reliably reconstruct a low rank matrix. We investigate the recovery abilities of the tested algorithms in the framework of phase transition, which compares the number of measurements, $m$, the size of an $n \times n$ matrix, $n^2$, and the minimum number of measurements needed to recover an $n \times n$ rank $r$ matrix $\mathbb{F}_d(2n - r)r$, through the undersampling and oversampling ratios

$$p = \frac{m}{n^2}, \quad q = \frac{(2n - r)r}{m}.$$  

The unit square $(p, q) \in [0, 1]^2$ defines a phase transition space. Given a triple $(n, m, r)$ corresponding to a fixed pair of $(p, q)$, we conducts test on ten random instances. The test rank $r$ matrix

---

2 All $n \times n$ rank $r$ matrices form a smooth embedded manifold of dimension $(2n - r)r$ in the ambient space $\mathbb{R}^{n^2}$.
is formed as the product of two random rank \( r \) matrices; that is \( X = LR \), where \( L \in \mathbb{R}^{n \times r} \) and \( R \in \mathbb{R}^{r \times n} \) with the entries of \( L \) and \( R \) sampled from the standard Gaussian distribution. The measurement vector \( P_\Omega(X) \) is obtained by sampling \( m \) entries of \( X \) uniformly at random. An algorithm is considered to have successfully recovered \( X \) if it returns a matrix \( X_l \) which satisfies

\[
\frac{\|X_l - X\|_F}{\|X\|_F} \leq 10^{-2}.
\]

The tests are conducted with \( n = 800 \) and \( p \) taking 18 equispaced values from 0.1 to 0.95.

The probabilities of successful recovery for the three tested algorithms RGrad, RCG and RCG restarted are displayed in Fig. 1. In the figure, white color indicates that the algorithm can recover all of the ten random test matrices while black color implies the algorithm fails to recover each of the randomly drawn matrices. For each tested algorithm, a clear phase transition occurs when \( q \) is greater than 0.9 for all the values of \( p \). This implies that all the three tested algorithms are able to recover a rank \( r \) matrix from \( m = C \cdot (2n - r)r \) number of measurements with \( C \) being slightly larger than 1. In addition, Fig. 1c also shows the effectiveness of our restarting conditions for the Riemannian conjugate gradient descent algorithm.

### 3.2 Computation Efficiency

We compare the computational efficiency of RGrad, RCG, RCG restarted by conducting random tests on matrices of \( 8000 \times 8000 \) and rank 100. The tests are conducted with two different over-sampling ratios \( 1/q \in \{2, 3\} \). The algorithms are terminated when the relative residual is less than \( 10^{-9} \). The relative residual plotted against the number of iterations and the average recovery time are presented in Fig. 2. First it can be observed that the convergence curves for RCG and RCG restarted are almost indistinguishable, differing only in one or two iterations. This again shows the effectiveness of our restarting conditions. A close look at the computational results reveals that restarting usually occurs in the first few iterations for RCG restarted. Moreover, RCG and RCG restarted are sufficiently faster than RGrad both in terms of the number of iterations and in terms of the average computation time. It takes less number of iterations for each algorithm to converge below the desired accuracy when the number of measurements increases.
Figure 2: Relative residual (mean and standard deviation over ten random tests) as function of number of iterations for \( n = 8000, r = 100, 1/q = 2 \) (a) and \( 1/q = 3 \) (b). The values after each algorithm are the average computational time (seconds) for convergence.

Figure 3: Performance of (a) RGrad, (b) RCG and (c) RCG restarted under different SNR.

### 3.3 Robustness to Additive Noise

Following the test set-up in last subsection, we further explore performance of the algorithms under the measurements with additive noise. Tests with additive noise have the sampled entries \( \mathcal{P}_\Omega(X) \) corrupted by the vector

\[
e = \sigma \cdot \| \mathcal{P}_\Omega(X) \|_F \cdot \frac{w}{\|w\|_2},
\]

where the entries of \( w \) are i.i.d standard Gaussian random variables and \( \sigma \) is referred to as noise level. We conduct tests with nine different values of \( \sigma \) from \( 10^{-4} \) to 1; and for each \( \sigma \), ten random tests are conducted. The average relative reconstruction error in dB plotted against the signal-to-noise ratio (SNR) is presented in Fig. 3 for RGrad, RCG and RCG restarted respectively. The plots clearly show the desirable linear scaling between the noise levels and the relative errors for all the three tested algorithms. The relative error decreases as the number of measurements increases.
4 Proofs

In this section, we prove the main results in Sec. 2. We first list several technical lemmas which are of independent interest. The proofs of these lemmas are presented in Appendix B.

4.1 Technical Lemmas

**Lemma 4.1** (Bounds for Projections). Let \(X_i = U_i \Sigma_i V_i^*\) be a rank \(r\) matrix, and \(T_i\) be the tangent space of the rank \(r\) matrix manifold at \(X_i\). Let \(X = U \Sigma V^*\) be another \(r\) matrix, and \(T\) be the corresponding tangent space. Then

\[
\|U_i U^*_i - UU^*\| \leq \frac{\|X_i - X\|_F}{\sigma_{\min}(X)}, \quad \|V_i V^*_i - VV^*\| \leq \frac{\|X_i - X\|_F}{\sigma_{\min}(X)},
\]

\[
\|U_i U^*_i - UU^*\|_F \leq \sqrt{2} \frac{\|X_i - X\|_F}{\sigma_{\min}(X)}, \quad \|V_i V^*_i - VV^*\|_F \leq \sqrt{2} \frac{\|X_i - X\|_F}{\sigma_{\min}(X)}, \quad (16)
\]

\[
\|\langle I - P_{T_i} \rangle X\|_F \leq \frac{\|X_i - X\|_F^2}{\sigma_{\min}(X)}, \quad \|P_{T_i} - P_{T}\| \leq \frac{2\|X_i - X\|_F}{\sigma_{\min}(X)}.
\]

**Lemma 4.2** (Restricted Isometry Property in a Local Neighborhood). Assume

\[
\|P_{\Omega}\| \leq \frac{8 \beta}{3} \log(n), \quad \|P_{T} - p^{-1}P_T P_{\Omega} P_{T}\| \leq \varepsilon_0, \quad \text{and} \quad \frac{\|X_i - X\|_F}{\sigma_{\min}(X)} \leq \frac{3p^{1/2} \varepsilon_0}{16 \beta \log(n)(1 + \varepsilon_0)}
\]

for some \(0 < \varepsilon_0 < 1\) and \(\beta > 1\). Then

\[
\|P_{\Omega} P_{T_i}\| \leq \frac{8 \beta}{3} \log(n)(1 + \varepsilon_0)p^{1/2}, \quad (17)
\]

\[
\|P_{T_i} - p^{-1}P_T P_{\Omega} P_{T_i}\| \leq 4\varepsilon_0. \quad (18)
\]

**Lemma 4.3** (Asymmetric Restricted Isometry Property). Let \(X_i = U_i \Sigma_i V_i^*\) and \(X = U \Sigma V^*\) be two fixed rank \(r\) matrices. Assume

\[
\|P_{U_i}(e_i)\| \leq \sqrt{\frac{\mu r}{n}} \quad \text{and} \quad \|P_{V_i}(e_j)\| \leq \sqrt{\frac{\mu r}{n}},
\]

\[
\|P_U(e_i)\| \leq \sqrt{\frac{\mu r}{n}} \quad \text{and} \quad \|P_V(e_j)\| \leq \sqrt{\frac{\mu r}{n}}
\]

for \(1 \leq i, j \leq n\). Suppose \(\Omega\) with \(|\Omega| = m\) is a set of indices sampled independently and uniformly with replacement. Then for any \(\beta > 1\),

\[
\left\| \frac{n^2}{m} P_{T_i} P_{\Omega}(P_U - P_{U_i}) - P_{T_i}(P_U - P_{U_i}) \right\| \leq \sqrt{\frac{48 \beta \mu nr \log(n)}{m}}
\]

with probability at least \(1 - 2n^{2-2\beta}\) provided \(m \geq 15 \beta \mu nr \log(n)\).

**Lemma 4.4** (A Recursive Relationship). Let \(\rho_1, \rho_2\) and \(\gamma\) be positive constants satisfying \(\rho_2 \geq \rho_1\). Define

\[
\tau_1 = \rho_1 + \gamma, \quad \tau_2 = (\rho_2 - \rho_1)\gamma, \quad \text{and} \quad \nu = \frac{1}{2} \left( \tau_1 + \sqrt{\tau_1^2 + 4\tau_2} \right).
\]
Let \( \{c_l\}_{l \geq 0} \) be a non-negative sequence satisfying \( c_1 \leq \nu c_0 \) and
\[
c_{l+1} \leq \rho_1 c_l + \rho_2 \sum_{j=0}^{l-1} \gamma^{l-j} c_j, \quad \forall \ l \geq 1.
\]

Then if \( \tau_1 + \tau_2 < 1 \), we have \( \nu < 1 \) and
\[
c_{l+1} \leq \nu^{l+1} c_0.
\]

**Lemma 4.5** (Chordal and Projection Distances). Let \( U, \ U \in \mathbb{R}^{n \times r} \) be two orthogonal matrices. Then there exists a \( r \times r \) unitary matrix \( Q \) such that
\[
\|U_i - UQ\|_F \leq \|U_i U_i^* - UU^*\|_F.
\]

### 4.2 Proof of Theorem 2.2

We start with a lemma which bounds the search stepsize \( \alpha_l \) in Alg. 4.

**Lemma 4.6.** Assume \( \|P_{T_i} - p^{-1}P_{T_i}P_{\Omega}P_{T_i}\| \leq 4\varepsilon_0 \). Then the stepsize \( \alpha_l \) in Alg. 4 can be bounded as
\[
\frac{1}{(1 + 4\varepsilon_0)p} \leq \alpha_l = \frac{\|P_{T_i}(G_l)\|_F^2}{\langle P_{T_i}(G_l), P_{\Omega}P_{T_i}(G_l) \rangle} \leq \frac{1}{(1 - 4\varepsilon_0)p}.
\]

**Proof.** First the assumption \( \|P_{T_i} - p^{-1}P_{T_i}P_{\Omega}P_{T_i}\| \leq 4\varepsilon_0 \) implies
\[
\|P_{T_i}P_{\Omega}P_{T_i}\| \leq p \|P_{T_i} - p^{-1}P_{T_i}P_{\Omega}P_{T_i}\| + p \|P_{T_i}\| \leq (1 + 4\varepsilon_0)p.
\]

On one hand,
\[
\langle P_{T_i}(G_l), P_{\Omega}P_{T_i}(G_l) \rangle = \langle P_{T_i}(G_l), P_{T_i}P_{\Omega}P_{T_i}(G_l) \rangle \leq (1 + 4\varepsilon_0)p \|P_{T_i}(G_l)\|_F^2,
\]
which implies the lower bound of \( \alpha_l \).

On the other hand,
\[
\|P_{T_i}(G_l)\|_F^2 = \langle P_{T_i}(G_l), P_{T_i}(G_l) - p^{-1}P_{T_i}P_{\Omega}P_{T_i}(G_l) \rangle + \langle P_{T_i}(G_l), p^{-1}P_{T_i}P_{\Omega}P_{T_i}(G_l) \rangle
\]
\[
\leq 4\varepsilon_0 \|P_{T_i}(G_l)\|_F^2 + p^{-1} \langle P_{T_i}(G_l), P_{\Omega}P_{T_i}(G_l) \rangle,
\]
from which we can obtain the upper bound of \( \alpha_l \) by multiplying \( p \) on both sides of the above inequality followed by the rearrangement.

The next lemma bounds the local isometry of \( P_{\Omega} \) when the adaptive stepsize \( \alpha_l \) is used.

**Lemma 4.7.** Assume \( \|P_{T_i} - p^{-1}P_{T_i}P_{\Omega}P_{T_i}\| \leq 4\varepsilon_0 \) and \( \alpha_l \) can be bounded as in Lem. 4.6. Then the spectral norm of \( P_{T_i} - \alpha_l P_{T_i}P_{\Omega}P_{T_i} \) can be bounded as
\[
\|P_{T_i} - \alpha_l P_{T_i}P_{\Omega}P_{T_i}\| \leq \frac{8\varepsilon_0}{1 - 4\varepsilon_0}.
\]
Proof. The lemma follows from direct calculations
\[
\|P_T - \alpha_l P_T P_{\Omega} P_T\| \leq \|P_T - p^{-1} P_T P_{\Omega} P_T\| + |\alpha_l - p^{-1}| \|P_T P_{\Omega} P_T\|
\]
\[
\leq 4\varepsilon_0 + \frac{4\varepsilon_0}{(1 - 4\varepsilon_0)p}(1 + 4\varepsilon_0)p
\]
\[
= \frac{8\varepsilon_0}{1 - 4\varepsilon_0},
\]
where the second inequality follows from the assumption and Lem. 4.6.

Proof of Theorem 2.2. We first assume that in the \(l\)-th iteration \(X_l\) satisfies
\[
\frac{\|X_l - X\|_F}{\sigma_{\min}(X)} \leq \frac{3p^{1/2}\varepsilon_0}{16\beta \log(n)(1 + \varepsilon_0)}
\]
(21)
So together with the first two assumptions (7) and (8) of Thm. 2.2, the application of Lem. 4.2 gives
\[
\|P_{\Omega} P_T\| \leq \frac{8\varepsilon_0}{3}\beta \log(n)(1 + \varepsilon_0)p^{1/2}
\]
(22)
and
\[
\|P_T - p^{-1} P_T P_{\Omega} P_T\| \leq 4\varepsilon_0,
\]
(23)
which means the assumptions of Lems. 4.6 and 4.7 are satisfied.
Recall that \(W_l = X_l + \alpha_l P_T (G_l)\) in Alg. 1. The proof begins with the following inequality
\[
\|X_{l+1} - X\|_F \leq \|X_{l+1} - W_l\|_F + \|W_l - X\|_F \leq 2\|W_l - X\|_F,
\]
where the second inequality follows from the fact that \(X_{l+1}\) is the best rank \(r\) approximation of \(W_l\). Plugging in \(W_l = X_l + \alpha_l P_T (G_l)\) gives
\[
\|X_{l+1} - X\|_F \leq 2\|X_l + \alpha_l P_T (G_l) - X\|_F
\]
\[
= 2\|X_l - X - \alpha_l P_T (X_l - X)\|_F
\]
\[
\leq 2\|\left((P_T - \alpha_l P_T P_{\Omega} P_T)(X_l - X)\right)\|_F
\]
\[
+ 2\|(I - P_T)(X_l - X)\|_F
\]
\[
+ 2|\alpha_l| \|P_T P_{\Omega} (I - P_T)(X_l - X)\|_F
\]
\[
:= I_1 + I_2 + I_3.
\]
(24)
First we have
\[
I_1 \leq \frac{16\varepsilon_0}{1 - 4\varepsilon_0} \|X_l - X\|_F
\]
and
\[
I_2 \leq \frac{2\|X_l - X\|_F^2}{\sigma_{\min}(X)} \leq \frac{3p^{1/2}\varepsilon_0}{8\beta \log(n)(1 + \varepsilon_0)} \|X_l - X\|_F \leq \frac{\varepsilon_0}{1 - 4\varepsilon_0} \|X_l - X\|_F
\]
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which follows from Lems. 4.7 and 4.11 respectively. The third term $I_3$ can be bounded as follows.

\[
I_3 \leq 2|\alpha_l| \|P_l P_{l_1}\| \|(I - P_{l_1})(X)\|_F
\leq \frac{2}{(1 - 4\varepsilon_0)^p} \frac{3}{\beta} \log(n)(1 + \varepsilon_0)p^{1/2} \frac{\|X_l - X\|_F^2}{\sigma_{\min}(X)}
\leq \frac{\varepsilon_0}{1 - 4\varepsilon_0} \|X_l - X\|_F,
\]

where the second inequality follows from (22), and Lems. 4.6 and 4.11 and the third inequality follows from (21).

So inserting the bounds for $I_1$, $I_2$ and $I_3$ into (21) gives

\[
\|X_{l+1} - X\|_F \leq \nu_2 \|X_l - X\|_F,
\]

where

\[
\nu_2 = \frac{18\varepsilon_0}{1 - 4\varepsilon_0} < 1
\]

by the assumption of Thm. 2.2.

It only remains to verify (21). By the assumption of Thm. 2.2 (21) is valid for $l = 0$. Since $\|X_l - X\|_F$ is a contractive sequence following from (25), (21) is valid for all $l \geq 0$ by induction. □

4.3 Proof of Theorem 2.3

We first estimate $\alpha_l$ and $\beta_l$ in Alg. 2 with the restarting conditions in (11).

Lemma 4.8. Assume $\|P_{l_1} - p^{-1}P_l P_{l_1}\| \leq 4\varepsilon_0$. When restarting occurs, $\beta_l = 0$ and $\alpha_l$ can be bounded as in Lem. 4.6, otherwise

\[
|\beta_l| \leq \varepsilon_{\beta} \quad \text{and} \quad |\alpha_l \cdot p - 1| \leq \varepsilon_{\alpha},
\]

where

\[
\varepsilon_{\beta} = \frac{4\kappa_2\varepsilon_0}{1 - 4\varepsilon_0} + \frac{\kappa_1\kappa_2}{1 - 4\varepsilon_0}, \quad \varepsilon_{\alpha} = \frac{4\varepsilon_0}{(1 - 4\varepsilon_0) - \kappa_1(1 + 4\varepsilon_0)}.
\]

Note that the bounds above are also valid even when restarting occurs since $\kappa_1 \geq 0$ and $\kappa_2 \geq 0$.

Proof. The orthogonalization weight $\beta_l$ can be bounded as follows

\[
|\beta_l| = \left| \frac{\langle P_{l_1}(G_l), P_{l_1} P_{l_1}(P_{l-1}) \rangle}{\langle P_{l_1}(P_{l-1}), P_{l_1} P_{l_1}(P_{l-1}) \rangle} \right|
\leq \frac{\langle P_{l_1}(G_l), (P_{l_1} P_{l_1} P_{l_1}(P_{l-1}) - p P_{l_1}(P_{l-1})) \rangle}{\langle P_{l_1}(P_{l-1}), P_{l_1} P_{l_1}(P_{l-1}) \rangle}
\leq \frac{4\varepsilon_0 p}{(1 - 4\varepsilon_0)p} \|P_{l_1}(G_l)\|_F + \frac{p}{(1 - 4\varepsilon_0)p} \|P_{l_1}(P_{l-1})\|_F
\leq \frac{4\kappa_2\varepsilon_0}{1 - 4\varepsilon_0} + \frac{1}{1 - 4\varepsilon_0} \|P_{l_1}(G_l)\|_F \|P_{l_1}(P_{l-1})\|_F \|P_{l_1}(P_{l-1})\|_F
\]

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\[
\leq \frac{4\kappa_2 \varepsilon_0}{1 - 4\varepsilon_0} + \frac{\kappa_1 \kappa_2}{1 - 4\varepsilon_0},
\]
where in the third line we used \( \langle P_{T_i}(P_{l-1}), P_{\Omega} P_{T_i}(P_{l-1}) \rangle \geq (1 - 4\varepsilon_0)p \| P_{T_i}(P_{l-1}) \|_F^2 \), deduced from (20), and the last two inequalities follow from the restarting conditions.

To bound \( \alpha_l \), we first need to bound \( \| P_{T_i}(G_i) \|_F \) in terms of \( \| P_{T_i}(P_l) \|_F \). Note that
\[
|\beta_l \langle P_{T_i}(G_i), P_{T_i}(P_{l-1}) \rangle| = \left| \frac{\langle P_{T_i}(G_i), P_{T_i} P_{\Omega} P_{T_i}(P_{l-1}) \rangle}{\langle P_{T_i}(P_{l-1}), P_{T_i} P_{\Omega} P_{T_i}(P_{l-1}) \rangle} \right| \langle P_{T_i}(G_i), P_{T_i}(P_{l-1}) \rangle \leq \frac{(1 + 4\varepsilon_0)p \| P_{T_i}(G_i) \|_F}{(1 - 4\varepsilon_0)p \| P_{T_i}(P_{l-1}) \|_F} \| P_{T_i}(G_i), P_{T_i}(P_{l-1}) \rangle \leq \frac{1 + 4\varepsilon_0}{1 - 4\varepsilon_0} \| P_{T_i}(G_i) \|_F \| P_{T_i}(P_{l-1}) \|_F \leq \frac{\kappa_1 (1 + 4\varepsilon_0)}{1 - 4\varepsilon_0} \| P_{T_i}(G_i) \|_F^2.
\]

So
\[
|\langle P_{T_i}(P_l), P_{T_i}(G_i) \rangle| = |\langle P_{T_i}(G_i) + \beta_l P_{T_i}(P_{l-1}), P_{T_i}(G_i) \rangle| \geq \| P_{T_i}(G_i) \|_F^2 - |\beta_l \langle P_{T_i}(G_i), P_{T_i}(P_{l-1}) \rangle| \geq \left( 1 - \frac{\kappa_1 (1 + 4\varepsilon_0)}{1 - 4\varepsilon_0} \right) \| P_{T_i}(G_i) \|_F^2.
\]

The application of the Cauchy-Schwarz inequality gives
\[
\| P_{T_i}(G_i) \|_F \leq \frac{1}{1 - \frac{\kappa_1 (1 + 4\varepsilon_0)}{1 - 4\varepsilon_0}} \| P_{T_i}(P_l) \|_F.
\]

Since \( \alpha_l \) can be rewritten as
\[
\alpha_l = \frac{\langle P_{T_i}(G_i), P_{T_i}(P_l) \rangle}{\langle P_{T_i}(P_l), P_{\Omega} P_{T_i}(P_l) \rangle} = \frac{\langle P_{T_i}(G_i), P_{T_i}^{-1} P_{\Omega} P_{T_i}(P_l) \rangle}{\langle P_{T_i}(P_l), P_{\Omega} P_{T_i}(P_l) \rangle} + \frac{\langle P_{T_i}(G_i), (P_{T_i} - P_{T_i}^{-1} P_{\Omega} P_{T_i})(P_l) \rangle}{\langle P_{T_i}(P_l), P_{\Omega} P_{T_i}(P_l) \rangle} = \frac{\langle P_{T_i}(G_i), P_{T_i}^{-1} P_{\Omega} P_{T_i}(P_l) \rangle}{\langle P_{T_i}(P_l), P_{\Omega} P_{T_i}(P_l) \rangle} + \frac{\langle P_{T_i}(G_i), (P_{T_i} - P_{T_i}^{-1} P_{\Omega} P_{T_i})(P_l) \rangle}{\langle P_{T_i}(P_l), P_{\Omega} P_{T_i}(P_l) \rangle} = p^{-1} + \frac{\langle P_{T_i}(G_i), (P_{T_i} - P_{T_i}^{-1} P_{\Omega} P_{T_i})(P_l) \rangle}{\langle P_{T_i}(P_l), P_{\Omega} P_{T_i}(P_l) \rangle},
\]

it can be bounded as follows
\[
|\alpha_l \cdot p - 1| \leq p \left| \frac{\langle P_{T_i}(G_i), (P_{T_i} - p^{-1} P_{T_i} P_{\Omega} P_{T_i})(P_l) \rangle}{\langle P_{T_i}(P_l), P_{\Omega} P_{T_i}(P_l) \rangle} \right| \leq \frac{4\varepsilon_0 p \| P_{T_i}(G_i) \|_F}{(1 - 4\varepsilon_0)p \| P_{T_i}(P_l) \|_F} \leq \frac{4\varepsilon_0}{(1 - 4\varepsilon_0) - \kappa_1 (1 + 4\varepsilon_0)},
\]
which completes the proof. \(\square\)
The following lemma bounds the local isometry of $P_{\Omega}$ when the adaptive stepsize $\alpha_l$ is used.

**Lemma 4.9.** Assume $\|P_{T_l} - p^{-1}P_{T_l}P_{\Omega}P_{T_l}\| \leq 4\varepsilon_0$, and $\alpha_l$ is bounded as in Lem. 4.8. Then the spectral norm of $P_{T_l} - \alpha_l P_{T_l}P_{\Omega}P_{T_l}$ can be bounded as

$$
\|P_{T_l} - \alpha_l P_{T_l}P_{\Omega}P_{T_l}\| \leq 4\varepsilon_0 + \varepsilon_\alpha(1 + 4\varepsilon_0).
$$

**Proof.** Direct calculations give

$$
\|P_{T_l} - \alpha_l P_{T_l}P_{\Omega}P_{T_l}\| \leq \|P_{T_l} - p^{-1}P_{T_l}P_{\Omega}P_{T_l}\| + \|\alpha_l - p^{-1}\|\|P_{T_l}P_{\Omega}P_{T_l}\|
\leq 4\varepsilon_0 + |\alpha_l - p^{-1}|\|p^{-1}P_{T_l}P_{\Omega}P_{T_l}\|
\leq 4\varepsilon_0 + \varepsilon_\alpha(1 + 4\varepsilon_0),
$$

which completes the proof. \hfill \square

**Proof of Theorem 2.3.** We first assume that for all $j \leq l$

$$
\|X_j - X\|_F \leq \frac{3p^{1/2}\varepsilon_0}{16\beta\log(n)(1 + \varepsilon_0)}. \tag{26}
$$

So together with the first two assumptions (7) and (8) of Thm. 2.3, the application of Lem. 4.2 gives

$$
\|P_{\Omega}P_{T_l}\| \leq \frac{8}{3}\beta\log(n)(1 + \varepsilon_0)p^{1/2} \tag{27}
$$

and

$$
\|P_{T_l} - p^{-1}P_{T_l}P_{\Omega}P_{T_l}\| \leq 4\varepsilon_0, \tag{28}
$$

which means the assumptions of Lems. 4.8 and 4.9 are satisfied for all $j \leq l$.

Analogous to (24), we have

$$
\|X_{l+1} - X\|_F \leq 2\|X_l + \alpha_l P_l - X\|_F
\leq 2\|X_l - X - \alpha_l P_{T_l}P_{\Omega}(X_l - X) + \alpha_l \beta_l P_{T_l}(P_l - 1)\|_F
\leq 2\|(P_{T_l} - \alpha_l P_{T_l}P_{\Omega}P_{T_l})(X_l - X)\|_F
\quad + 2\|(I - P_{T_l})(X_l - X)\|_F
\quad + 2|\alpha_l|\|P_{T_l}P_{\Omega}(I - P_{T_l})(X_l - X)\|_F
\quad + 2|\alpha_l||\beta_l|\|P_{T_l}(P_l - 1)\|_F
\quad := I_4 + I_5 + I_6 + I_7. \tag{29}
$$

Following the argument for the proof of Thm. 2.2, the first three terms can be similarly bounded as follows

$$
I_4 \leq (8\varepsilon_0 + 2\varepsilon_\alpha(1 + 4\varepsilon_0))\|X_l - X\|_F,
$$

$$
I_5 \leq \frac{\varepsilon_0}{1 - 4\varepsilon_0}\|X_l - X\|_F \leq (1 + \varepsilon_\alpha)\varepsilon_0\|X_l - X\|_F,
$$

$$
I_6 \leq (1 + \varepsilon_\alpha)\varepsilon_0\|X_l - X\|_F.
$$

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To bound $I_7$, first note that $\beta_i P_{T_i}(P_{l-1})$ can be expressed in terms of all the previous gradients

$$
\beta_i P_{T_i}(P_{l-1}) = \sum_{j=0}^{l-1} \left( \prod_{i=j+1}^{l} \beta_i \right) \left( \prod_{k=j}^{l-1} P_{T_k} \right) (G_j).
$$

So

$$
I_7 \leq 2|\alpha| \sum_{j=0}^{l-1} \left( \prod_{i=j+1}^{l} \beta_i \right) \left( \prod_{k=j}^{l-1} P_{T_k} \right) (G_j) \|_F,
$$

$$
= 2|\alpha| \sum_{j=0}^{l-1} \varepsilon_{\beta}^{l-j} \| P_{T_j} (G_j) \|_F,
$$

$$
\leq 2|\alpha| \sum_{j=0}^{l-1} \varepsilon_{\beta}^{l-j} \left( \| P_{T_j} P_{\Omega} P_{T_j} (X_j - X) \|_F + \| P_{T_j} P_{\Omega} (I - P_{T_j}) (X_j - X) \|_F \right),
$$

$$
\leq 2|\alpha| \sum_{j=0}^{l-1} \varepsilon_{\beta}^{l-j} \left( \| P_{T_j} P_{\Omega} P_{T_j} (X_j - X) \|_F + \| P_{T_j} \| \frac{\| X_j - X \|_F^2}{\sigma_{\min}(X)} \right),
$$

$$
\leq \frac{1 + \varepsilon_0}{p} \sum_{j=0}^{l-1} \varepsilon_{\beta}^{l-j} (2(1 + 4\varepsilon_0) p \| X_j - X \|_F + p \varepsilon_0 \| X_j - X \|_F),
$$

$$
= (1 + \varepsilon_0) \sum_{j=0}^{l-1} \varepsilon_{\beta}^{l-j} (2(1 + 4\varepsilon_0) + \varepsilon_0) \| X_j - X \|_F,
$$

where the second inequality follows from the bound for $\beta_i$ in Lem. 4.8 and the fact

$$
\left\| \left( \prod_{k=j}^{l-1} P_{T_k} \right) (G_j) \right\|_F \leq \| P_{T_j} (G_j) \|_F,
$$

the fourth inequality follows from Lem. 4.1 and the last inequality follows from the bound for $\alpha_l$ in Lem. 4.8 (26), (27), and (28).

Inserting the bounds for $I_4$, $I_5$, $I_6$ and $I_7$ into (29) gives

$$
\| X_{l+1} - X \|_F \leq (10\varepsilon_0 + 2\varepsilon_\alpha (1 + 5\varepsilon_0)) \| X_l - X \|_F + (1 + \varepsilon_\alpha)(2(1 + 4\varepsilon_0) + \varepsilon_0) \sum_{j=0}^{l-1} \varepsilon_{\beta}^{l-j} \| X_j - X \|_F,
$$

$$
\leq (10\varepsilon_0 + 2\varepsilon_\alpha (1 + 5\varepsilon_0)) \| X_l - X \|_F + (2 + 10\varepsilon_0 + 2\varepsilon_\alpha (1 + 5\varepsilon_0)) \sum_{j=0}^{l-1} \varepsilon_{\beta}^{l-j} \| X_j - X \|_F
$$

$$
:= \rho_1 \| X_l - X \|_F + \rho_2 \sum_{j=0}^{l-1} \varepsilon_{\beta}^{l-j} \| X_j - X \|_F.
$$
Define
\[ \tau_1 = \rho_1 + \varepsilon \beta = \frac{18\varepsilon_0 - 10\varepsilon_0\kappa_1(1 + 4\varepsilon_0)}{(1 - 4\varepsilon_0) - \kappa_1(1 + 4\varepsilon_0)} + \frac{4\kappa_2\varepsilon_0 + \kappa_1\kappa_2}{1 - 4\varepsilon_0}, \]
\[ \tau_2 = (\rho_2 - \rho_1)\varepsilon \beta = \frac{8\kappa_2\varepsilon_0 + 2\kappa_1\kappa_2}{1 - 4\varepsilon_0}, \]
\[ \nu_{cg} = \frac{1}{2} \left( \tau_1 + \sqrt{\tau_1^2 + \tau_2} \right). \]

When \( l = 0 \), Alg. 2 is the same as Alg. 1, so
\[ \|X_1 - X\|_F \leq \frac{18\varepsilon_0}{1 - 4\varepsilon_0} \|X_0 - X\|_F \leq \nu_{cg} \|X_0 - X\|_F, \]
following from (25). Therefore Lem. 4.4 implies if \( \tau_1 + \tau_2 < 1 \), we have \( \nu_{cg} < 1 \) and
\[ \|X_{l+1} - X\|_F \leq \nu_{cg}^{l+1} \|X_0 - X\|_F. \]
Similarly, (26) is only required at \( l = 0 \) since we have a contractive sequence.

4.4 Proof of Lemma 2.4

Let \( W_0 = p - 1\mathcal{P}_\Omega(X) \). First we have
\[ \|X_0 - X\| \leq \|X_0 - W_0\| + \|W_0 - X\| \leq 2 \|W_0 - X\| \leq 2 \sqrt{\frac{8\beta n^3 \log(n)}{3m}} \|X\|_\infty, \]
where the last inequality holds true with probability at least \( 1 - 2n^{1-\beta} \) following from Thm. A.3. Consequently,
\[ \|X_0 - X\|_F \leq \sqrt{2r} \|X_0 - X\| \leq \sqrt{\frac{64\beta n^3 r \log(n)}{3m}} \|X\|_\infty \leq \sqrt{\frac{64\beta \mu r^2 \log(n)}{3m}} \|X\|, \]
which completes the proof.

4.5 Proof of Lemma 2.6

We first present a lemma which says the matrix returned by Alg. 4 is incoherent and its approximation error can be bounded by the approximation error of the input matrix.

Lemma 4.10. Let \( Z_l = U_l \Sigma_l V_l^* \) be a rank \( r \) matrix such that
\[ \|Z_l - X\|_F \leq \frac{\sigma_{\min}(X)}{10\sqrt{2}}. \]
Then the matrix \( \tilde{Z}_l \) returned by Alg. 4 satisfies
\[ \| \mathcal{P}_{\hat{U}_l}(e_i) \| \leq \frac{10}{9} \sqrt{\frac{\mu \rho^r}{n}} \quad \text{and} \quad \| \mathcal{P}_{\hat{V}_l}(e_j) \| \leq \frac{10}{9} \sqrt{\frac{\mu \rho^r}{n}} \]
for \( 1 \leq i, j \leq n \), where the columns of \( \hat{U}_l \) and \( \hat{V}_l \) are the right and left singular vectors of \( \tilde{Z}_l \) respectively. Furthermore,
\[ \| \tilde{Z}_l - X \|_F \leq 8\kappa \|Z_l - X\|_F. \]
Proof. For simplicity, let \( d = \|Z_l - X\|_F \). By Lem. 4.4, we have

\[
\|U_l U_l^* - UU^*\|_F \leq \frac{\sqrt{2d}}{\sigma_{\min}(X)} \quad \text{and} \quad \|V_l V_l^* - VV^*\|_F \leq \frac{\sqrt{2d}}{\sigma_{\min}(X)}.
\]

This together with Lem. 4.5 implies that there exist two unitary matrices \( Q_u \in \mathbb{R}^{r \times r} \) and \( Q_v \in \mathbb{R}^{r \times r} \) such that

\[
\|U_l - U Q_u\|_F \leq \frac{\sqrt{2d}}{\sigma_{\min}(X)} \quad \text{and} \quad \|V_l - V Q_v\|_F \leq \frac{\sqrt{2d}}{\sigma_{\min}(X)}.
\]

It follows that

\[
\|\Sigma_l - Q_u^* \Sigma Q_v\|_F = \|U_l^* Z_l V_l - (U Q_u)^* X (V Q_v)\|_F \\
\leq \|U_l^* Z_l V_l - (U Q_u)^* Z_l V_l\|_F + \|((U Q_u)^* Z_l V_l - (U Q_u)^* X V_l)\|_F \\
= \|U_l - U Q_u\|_F \|Z_l\| + \|Z_l - X\|_F + \|X\| \|V_l - V Q_v\|_F \\
\leq \frac{\sqrt{2d}(d + \sigma_{\max}(X))}{\sigma_{\min}(X)} + d + \frac{\sqrt{2d} \sigma_{\max}(X)}{\sigma_{\min}(X)} \\
\leq 4 \kappa d,
\]

where \( \kappa \) is the condition number of \( X \), and we have used the assumption \( d \leq \sigma_{\min}(X)/10\sqrt{2} \leq \sigma_{\max}(X)/10\sqrt{2} \) and the fact

\[
\|Z_l\| \leq \|X\| + \|Z_l - X\| \leq \sigma_{\max}(X) + d.
\]

in the last two inequalities.

Recall that \( A_l \) and \( B_l \) in Alg. 4 are defined as

\[
A_l^{(i)} = \min \left( \frac{\mu_0 r}{n}, \sqrt{\frac{\mu_0 r}{n}} \right), \quad \text{and} \quad B_l^{(i)} = \min \left( \frac{\mu_0 r}{n}, \sqrt{\frac{\mu_0 r}{n}} \right).
\]

Because

\[
\|(U Q_u)^{(i)}\| \leq \sqrt{\frac{\mu_0 r}{n}} \quad \text{and} \quad \|(V Q_v)^{(i)}\| \leq \sqrt{\frac{\mu_0 r}{n}},
\]

we have

\[
\|A_l^{(i)} - (U Q_u)^{(i)}\| \leq \|U_l^{(i)} - (U Q_u)^{(i)}\| \quad \text{and} \quad \|B_l^{(i)} - (V Q_v)^{(i)}\| \leq \|V_l^{(i)} - (V Q_v)^{(i)}\|.
\]

Therefore

\[
\|A_l - U Q_u\|_F \leq \|U_l - U Q_u\|_F \leq \frac{\sqrt{2d}}{\sigma_{\min}(X)}, \quad \text{and} \quad (31)
\]

\[
\|B_l - V Q_v\|_F \leq \|V_l - V Q_v\|_F \leq \frac{\sqrt{2d}}{\sigma_{\min}(X)}.
\]

(32)
Since \( \hat{Z}_l = A_l \Sigma_i B_i^* \) by Alg. 4, we have
\[
\left\| \hat{Z}_l - X \right\|_F = \left\| A_l \Sigma_i B_i^* - (U Q_u)(Q_u^* \Sigma Q_v)(V Q_v)^* \right\|_F \\
\leq \left\| A_l \Sigma_i B_i^* - (U Q_u) \Sigma_i B_i^* \right\|_F + \left\| (U Q_u) \Sigma_i B_i^* - (U Q_u)(Q_u^* \Sigma Q_v) B_i^* \right\|_F \\
+ \left\| (U Q_u)(Q_u^* \Sigma Q_v) B_i^* - (U Q_u)(Q_u^* \Sigma Q_v)(V Q_v)^* \right\|_F \\
\leq \left\| A_l - U Q_u \right\|_F \left\| \Sigma_i \right\| \left\| B_i \right\| + \left\| \Sigma_i - Q_u^* \Sigma Q_v \right\|_F \left\| B_i \right\| + \left\| \Sigma \right\| \left\| B_l - V Q_v \right\|_F \\
\leq \frac{\sqrt{2}d}{\sigma_{\text{min}}(X)} (\sigma_{\text{max}}(X) + d) \left( \frac{\sqrt{2}d}{\sigma_{\text{min}}(X)} + 1 \right) + 4kd \left( \frac{\sqrt{2}d}{\sigma_{\text{min}}(X)} + 1 \right) + \sigma_{\text{max}}(X) \frac{\sqrt{2}d}{\sigma_{\text{min}}(X)} \\
\leq 8kd,
\]
where in the last two inequalities we use (30), the assumption \( d \leq \sigma_{\text{min}}(X)/10 \sqrt{2} \leq \sigma_{\text{max}}(X)/10 \sqrt{2} \) and the fact
\[
\left\| \Sigma_i \right\| = \left\| Z_l \right\| \leq \left\| X \right\| + \left\| Z_l - X \right\| \leq \sigma_{\text{max}}(X) + d.
\]

It remains to estimate the incoherence of \( \hat{Z}_l \). Because \( A_l \) and \( B_l \) are not necessarily orthogonal, we consider their QR factorizations:
\[
A_l = \widetilde{U}_l R_u \quad \text{and} \quad B_l = \widetilde{V}_l R_v.
\]

First note that
\[
\sigma_{\text{min}}(A_l) \geq 1 - \left\| A_l - U Q_u \right\| \geq 1 - \frac{\sqrt{2}d}{\sigma_{\text{min}}(X)} \geq \frac{9}{10},
\]
\[
\sigma_{\text{min}}(B_l) \geq 1 - \left\| B_l - V Q_v \right\| \geq 1 - \frac{\sqrt{2}d}{\sigma_{\text{min}}(X)} \geq \frac{9}{10}
\]
following from (31), (32), the assumption \( d \leq \sigma_{\text{min}}(X)/10 \sqrt{2} \) and the Weyl inequality. Therefore
\[
\left\| R_u^{-1} \right\| \leq \frac{10}{9} \quad \text{and} \quad \left\| R_v^{-1} \right\| \leq \frac{10}{9}.
\]

Consequently,
\[
\left\| \widetilde{U}_l^{(i)} \right\| = \left\| \widetilde{V}_l^{(i)} \right\| = \left\| A_l^{(i)} R_u^{-1} \right\| \leq \frac{10}{9} \sqrt{\frac{\mu_0 r}{n}} \quad \text{and} \quad \left\| \widetilde{V}_l^{(i)} \right\| = \left\| B_l^{(i)} R_v^{-1} \right\| \leq \frac{10}{9} \sqrt{\frac{\mu_0 r}{n}}
\]
following from the construction of \( A_l \) and \( B_l \).

\( \square \)

Proof of Lemma 2.6. First assume that
\[
\left\| Z_l - X \right\|_F \leq \frac{\sigma_{\text{min}}(X)}{256 \kappa^2}.
\]

It follows immediately from Lem. 4.10 that \( \hat{Z}_l \) is an incoherent matrix with the incoherence parameter \( \frac{100}{81} \mu_0 \) and
\[
\left\| \hat{Z}_l - X \right\|_F \leq 8 \kappa \left\| Z_l - X \right\|_F.
\]

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Analogous to (24), the approximation error at the \((l+1)\)th iteration can be decomposed as follows

\[
\|Z_{l+1} - X\|_F \leq 2 \left\| \left( \mathcal{P}_{\tilde{T}_l} - \frac{n^2}{m} \mathcal{P}_{\tilde{T}_l} \mathcal{P}_{\Omega_{l+1}} \mathcal{P}_{\tilde{T}_l} \right) (\tilde{Z}_l - X) \right\|_F \\
+ 2 \left\| (\mathcal{I} - \mathcal{P}_{\tilde{T}_l}) (\tilde{Z}_l - X) \right\|_F \\
+ 2 \left\| \frac{n^2}{m} \mathcal{P}_{\tilde{T}_l} \mathcal{P}_{\Omega_{l+1}} (\mathcal{I} - \mathcal{P}_{\tilde{T}_l}) (\tilde{Z}_l - X) \right\|_F \\
:= I_8 + I_9 + I_{10}.
\]  

(34)

Since \(\tilde{Z}_l\) (and consequently \(\tilde{T}_l\)) is independent of \(\Omega_{l+1}\), Thm. A.2 implies

\[
\left\| \mathcal{P}_{\tilde{T}_l} - \frac{n^2}{m} \mathcal{P}_{\tilde{T}_l} \mathcal{P}_{\Omega_{l+1}} \mathcal{P}_{\tilde{T}_l} \right\| \leq \sqrt{\frac{3200 \beta \mu_0 n r \log(n)}{243 m}}.
\]

with probability at least \(1 - 2n^{2-2}\beta\). So

\[
I_8 \leq 2 \sqrt{\frac{3200 \beta \mu_0 n r \log(n)}{243 m}} \left\| \tilde{Z}_l - X \right\|_F \\
\leq 16 \kappa \sqrt{\frac{3200 \beta \mu_0 n r \log(n)}{243 m}} \left\| Z_l - X \right\|_F.
\]

For \(I_9\), Lem. A.3 implies

\[
I_9 \leq \frac{2 \left\| \tilde{Z}_l - X \right\|_F^2}{\sigma_{\min}(X)} \leq \frac{128 \kappa^2 \left\| Z_l - X \right\|_F^2}{\sigma_{\min}(X)} \leq \frac{1}{2} \left\| Z_l - X \right\|_F,
\]

where the last inequality follows from (33).

To bound \(I_{10}\), note again \(\tilde{Z}_l\) (and consequently \(\tilde{T}_l\)) is independent of \(\Omega_{l+1}\) with the incoherence parameter \(\frac{100}{\kappa} \mu_0\). So Lem. A.3 implies

\[
\left\| \frac{n^2}{m} \mathcal{P}_{\tilde{T}_l} \mathcal{P}_{\Omega_{l+1}} (\mathcal{P}_U - \mathcal{P}_{\tilde{U}_l}) - \mathcal{P}_{\tilde{T}_l} (\mathcal{P}_U - \mathcal{P}_{\tilde{U}_l}) \right\| \leq \sqrt{\frac{4800 \beta \mu_0 n r \log(n)}{81 m}}.
\]

with probability at least \(1 - 2n^{2-2\beta}\). Since

\[
(\mathcal{I} - \mathcal{P}_{\tilde{T}_l})(\tilde{Z}_l - X) = - (\mathcal{I} - \mathcal{P}_{\tilde{T}_l})(X) \\
= - UU^* X + \tilde{U}_l \tilde{U}_l^* X + UU^* X \tilde{V}_l \tilde{V}_l^* = - (UU^* - \tilde{U}_l \tilde{U}_l^*) X (I - \tilde{V}_l \tilde{V}_l^*) \\
= (UU^* - \tilde{U}_l \tilde{U}_l^*) (\tilde{Z}_l - X) (I - \tilde{V}_l \tilde{V}_l^*) \\
= (\mathcal{P}_U - \mathcal{P}_{\tilde{U}_l})(\mathcal{I} - \mathcal{P}_{\tilde{V}_l})(\tilde{Z}_l - X),
\]

we have

\[
I_{10} = 2 \left\| \frac{n^2}{m} \mathcal{P}_{\tilde{T}_l} \mathcal{P}_{\Omega_{l+1}} (\mathcal{P}_U - \mathcal{P}_{\tilde{U}_l})(\mathcal{I} - \mathcal{P}_{\tilde{V}_l})(\tilde{Z}_l - X) \right\|_F
\]

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\[
\begin{align*}
2 \| n^2 \hat{m} P_T \Omega_{l+1} (P_U - P_U)(I - P_{\hat{U}})(\hat{Z}_l - X) - P_{\hat{T}} (P_U - P_{\hat{U}})(I - P_{\hat{V}})(\hat{Z}_l - X) \|_F \\
&\leq 2 \| n^2 \hat{m} P_T \Omega_{l+1} (P_U - P_U) - P_{\hat{T}} (P_U - P_{\hat{U}}) \|_F \| \hat{Z}_l - X \|_F \\
&\leq 2 \sqrt{\frac{4800 \beta \mu_0 nr \log(n)}{81 \hat{m}}} \| \hat{Z}_l - X \|_F \\
&\leq 16 \kappa \sqrt{\frac{4800 \beta \mu_0 nr \log(n)}{81 \hat{m}}} \| Z_l - X \|_F .
\end{align*}
\]
where the second equality follows from
\[
\begin{align*}
P_{\hat{T}} (P_U - P_{\hat{U}})(I - P_{\hat{V}})(\hat{Z}_l - X) &= P_{\hat{T}} (I - P_{\hat{U}})(\hat{Z}_l - X) = 0.
\end{align*}
\]

Putting the bounds for \( I_8, I_9 \) and \( I_{10} \) together gives
\[
\| Z_{l+1} - X \|_F \leq \left( \frac{1}{2} + 182 \kappa \sqrt{\frac{\beta \mu_0 nr \log(n)}{\hat{m}}} \right) \| Z_l - X \|_F
\]
\[
\leq \frac{5}{6} \| Z_l - X \|_F
\]
with probability at least \( 1 - 4 n^{2-2\beta} \) provided
\[
\hat{m} \geq C \beta \mu_0 \kappa^2 nr \log(n) \tag{35}
\]
with \( C \) being sufficiently large. Clearly (33) is also valid for \((l+1)\)th iteration.

Since \( Z_0 = H_{\sigma} \left( \frac{\hat{m}}{n} P_{\Omega_0} (X) \right) \), (33) is valid for \( l = 0 \) with probability \( 1 - 2 n^{1-\beta} \) provided
\[
\hat{m} \geq C \beta \mu_0^2 \kappa^6 nr^2 \log(n) \tag{36}
\]
following from Lem. 2.4. Therefore taking a maximum of the right hand sides of (35) and (36) gives
\[
\| Z_L - X \|_F \leq \left( \frac{5}{6} \right)^L \frac{\sigma_{\min} (X)}{256 \kappa^2}
\]
with probability at least \( 1 - 2 n^{1-\beta} - 4 Ln^{2-2\beta} \) provided
\[
\hat{m} \geq C \beta \max \{ \mu_0, \mu_1 \} \kappa^6 nr^2 \log(n).
\]

5 Conclusion and Future Direction

This manuscript presents the sampling complexity for a class of Riemannian gradient descent and conjugate gradient descent algorithms by interpreting them as iterative hard thresholding algorithms with subspace projections. To the best of our knowledge, this is the first work that provides recovery guarantees of the Riemannian optimization algorithms on the embedded low
rank matrix manifold for matrix completion. Our first sampling complexity for the algorithms with one step hard thresholding initialization is $O(n^{1.5}r^{\log^{1.5}}(n))$. We would like to know whether this result can be improved to the nearly optimal one $O(nr \text{polylog}(n))$ since the simulation results in Sec. 3.1 strongly suggests so. The extra $r$ term in the second recovery guarantee result comes from bounding the matrix spectral norm by the Frobenius norm. To further optimize the second sampling complexity, we may need to establish convergence of the algorithms in terms of the matrix spectral norm rather than the Frobenius norm.

It would be of interest to investigate whether we can extend our results to the case whether the unknown matrix is approximately low rank. Since in this case $\mathcal{P}_\Omega(X)$ can be decomposed as $\mathcal{P}_\Omega(X) = \mathcal{P}_\Omega(X_r) + \mathcal{P}_\Omega(X - X_r)$, where $X_r$ is the best rank $r$ approximation of $X$, it is equivalent to study the robustness of the algorithms under additive noise which is interesting by itself. The empirical observations in Sec. 3.3 suggests that both the Riemannian gradient descent and conjugate gradient descent algorithms are very robust under additive Gaussian white noise. Robustness analysis of the algorithms is scope for future work. It would also be desirable to consider more general and practical sampling models in matrix completion for the Riemannian optimization algorithms (Algs. 1 and 2).

The Riemannian gradient descent and conjugate gradient descent algorithms presented in this manuscript apply equally to other low rank reconstruction problems, such as phase retrieval [20, 10, 11, 48, 16, 41] and blind deconvolution [3, 32]. This line of research will be pursued independently in the future. Since the condition number of a rank one matrix is always equal to one, it is worth investigating whether we can obtain recovery guarantees of the form $O(n \text{polylog}(n))$ with a universal constant.

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A Supplementary Results

In this section, we will list the tail probability bounds from the literature which have been used in this manuscript. We start with the Noncommutative Bernstein inequality.

**Theorem A.1** (Noncommutative Bernstein Inequality, [2, 38]). Let $Z_1, \cdots, Z_L$ be $n \times n$ independent zero-mean random matrices. Suppose $\sigma^2_k = \max\{\|E[Z_k Z_k^*]\|, \|E[Z_k^* Z_k]\|\}$ and $\|Z_k\| \leq R$ almost surely for all $k$. Then for any $t > 0$,

$$\Pr\left[\left\| \sum_{k=1}^L Z_k \right\| > t \right] \leq 2n \exp\left( \frac{-t^2/2}{\sum_{k=1}^L \sigma_k^2 + Rt/3} \right).$$
Moreover, if \( t \leq \frac{1}{n} \sum_{k=1}^{L} \sigma_{k}^{2} \),

\[
\mathbb{P} \left[ \left\| \sum_{k=1}^{L} Z_{k} \right\| > t \right] \leq 2n \exp \left( \frac{3t^{2}}{8 \sum_{k=1}^{L} \sigma_{k}^{2}} \right).
\]

Two tail probability bounds for \( \mathcal{P}_{\Omega} \) can be obtained using the Noncommutative Bernstein inequality under the sampling with replacement model.

**Theorem A.2** ([38, 22, 13]). Suppose \( \Omega \) with \( |\Omega| = m \) is a set of indices sampled independently and uniformly with replacement. Let \( X = U \Sigma V^{*} \in \mathbb{R}^{n \times n} \) be a rank \( r \) matrix with the corresponding tangent space \( T \). Assume

\[
\| \mathcal{P}_{U} (e_{i}) \| \leq \sqrt{\frac{\mu r}{n}} \quad \text{and} \quad \| \mathcal{P}_{V} (e_{j}) \| \leq \sqrt{\frac{\mu r}{n}}
\]

for \( 1 \leq i, j \leq n \). Then for all \( \beta > 1 \),

\[
\left\| \mathcal{P}_{T} - \frac{n^{2}}{m} \mathcal{P}_{\Omega} \mathcal{P} \right\| \leq \sqrt{\frac{32 \beta \mu n^{r} \log(n)}{3m}}
\]

with probability at least \( 1 - 2n^{2} - 2^{\beta} \) provided \( m \geq \frac{32}{7} \beta \mu n^{r} \log(n) \).

**Theorem A.3** ([38, 22, 13]). Suppose \( \Omega \) with \( |\Omega| = m \) is a set of indices sampled independently and uniformly with replacement. Let \( Z \in \mathbb{R}^{n \times n} \) be a fixed matrix. Then for all \( \beta > 1 \),

\[
\left\| \left( \frac{n^{2}}{m} \mathcal{P}_{\Omega} - I \right) (Z) \right\| \leq \sqrt{\frac{8 \beta n^{3} \log(n)}{3m}} \| Z \|_{\infty}
\]

with probability \( 1 - 2n^{1-\beta} \) provided \( m \geq 6 \beta n \log(n) \).

**B Proofs of Technical Lemmas**

**B.1 Proof of Lemma 4.1**

The proofs for the first five inequalities in this lemma can be found in [49]. So it only remains to prove the last inequality. For any matrix \( Z \in \mathbb{R}^{n \times n} \), we have

\[
(\mathcal{P}_{T_{i}} - \mathcal{P}_{T}) (Z) = U_{i} U_{i}^{*} Z + ZV_{i} V_{i}^{*} - U_{i} U_{i}^{*} ZV_{i} V_{i}^{*} - UU^{*} Z - ZV V^{*} + UU^{*} ZV V^{*}
\]

\[
= (U_{i} U_{i}^{*} - UU^{*}) Z(I - V V^{*}) + (I - U_{i} U_{i}^{*}) Z(V V_{i}^{*} - V V^{*}).
\]

Taking the Frobenius norm on both sides gives

\[
\left\| (\mathcal{P}_{T_{i}} - \mathcal{P}_{T}) (Z) \right\|_{F} \leq \left\| U_{i} U_{i}^{*} - UU^{*} \right\| \left\| Z \right\|_{F} \left\| I - V V^{*} \right\| + \left\| I - U_{i} U_{i}^{*} \right\| \left\| Z \right\|_{F} \left\| V V_{i}^{*} - V V^{*} \right\|
\]

\[
\leq \frac{2 \left\| X_{i} - X \right\|_{F}}{\sigma_{\min} (X)} \left\| Z \right\|_{F}.
\]
B.2 Proof of Lemma 4.2

For any $Z \in \mathbb{R}^{n \times n}$, we have

$$\|P_\Omega P_T(Z)\|_F^2 = (P_\Omega P_T(Z), P_\Omega P_T(Z))$$

$$\leq \frac{8}{3} \beta \log(n) (P_T(Z), P_\Omega P_T(Z))$$

$$= \frac{8}{3} \beta \log(n) (P_T(Z), P_T P_\Omega P_T(Z))$$

$$\leq \frac{8}{3} \beta \log(n) (1 + \varepsilon_0) \|P_T(Z)\|_F^2,$$

where the first inequality follows from the first assumption and the second inequality follows from the second assumption. So we have $\|P_\Omega P_T\| \leq \sqrt{\frac{8}{3} \beta \log(n)} (1 + \varepsilon_0) p$ and

$$\|P_\Omega P_T\| \leq \|P_\Omega (P_{T_1} - P_T)\| + \|P_\Omega P_T\|$$

$$\leq \frac{8}{3} \beta \log(n) \frac{2}{\sigma_{\min}(X)} \|X - X\|_F + \|P_\Omega P_T\|$$

$$\leq \frac{p^{1/2} \varepsilon_0}{1 + \varepsilon_0} + \sqrt{\frac{8}{3} \beta \log(n)} (1 + \varepsilon_0) p$$

$$\leq \frac{8}{3} \beta \log(n) (1 + \varepsilon_0) p^{1/2},$$

where the second inequality follows from (16). To prove (18), we use

$$\|P_{T_1} - p^{-1} P_{T_1} P_\Omega P_T\| \leq \|P_{T_1} - P_T\| + p^{-1} \|P_{T_1} P_\Omega P_T - P_T P_\Omega P_T\|$$

$$+ p^{-1} \|P_{T_1} P_\Omega P_T - P_T P_\Omega P_T\| + \|P_T - p^{-1} P_T P_\Omega P_T\|$$

$$\leq \|P_{T_1} - P_T\| + p^{-1} \|P_{T_1} P_\Omega P_T - P_T P_\Omega P_T\|$$

$$+ p^{-1} \|P_{T_1} P_\Omega P_T - P_T P_\Omega P_T\| + \|P_T - p^{-1} P_T P_\Omega P_T\|$$

$$\leq 2 \frac{\|X - X\|_F}{\sigma_{\min}(X)} + p^{-1} \|P_\Omega P_T\| \frac{2 \|X - X\|_F}{\sigma_{\min}(X)}$$

$$+ p^{-1} \|P_\Omega P_T\| \frac{2 \|X - X\|_F}{\sigma_{\min}(X)} + \|P_T - p^{-1} P_T P_\Omega P_T\|$$

$$\leq 4 \varepsilon_0,$$

where in the second inequality we utilize the fact $P_\Omega^* = P_\Omega$ so that $\|P_{T_1} P_\Omega\| = \|P_\Omega P_{T_1}\|$; and the last inequality follows from the assumption and the bounds for $\|P_\Omega P_{T_1}\|$ and $\|P_\Omega P_T\|$. 

B.3 Proof of Lemma 4.3

Lemma 4.3 is an asymmetric version of Thm. A.2. We will use the Noncommutative Bernstein inequality (Thm. A.1) to prove it. Let $\Omega = \{(i_k, j_k)\}_{k=1}^m$ be the sampled set of indices. For any $Z \in \mathbb{R}^{n \times n}$, since

$$(P_U - P_{U_i}) (Z) = \sum_{i,j=1}^n \langle (P_U - P_{U_i}) (Z), e_i e_j^* \rangle e_i e_j^* = \sum_{i,j=1}^n \langle Z, (P_U - P_{U_i}) (e_i e_j^*) \rangle e_i e_j^*,$$

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we have

\[
P_{\Omega} (P_U - P_{U_l}) (Z) = \sum_{k=1}^{m} \langle Z, (P_U - P_{U_l}) (e_{ik} e_{jk}^*) \rangle e_{ik} e_{jk}^*
\]

and

\[
P_{T_i} P_{\Omega} (P_U - P_{U_l}) (Z) = \sum_{k=1}^{m} \langle Z, (P_U - P_{U_l}) (e_{ik} e_{jk}^*) \rangle P_{T_i} (e_{ik} e_{jk}^*) .
\]

Let \( T_{ik,jk} : \mathbb{R}^{n \times n} \to \mathbb{R}^{n \times n} \) be a rank one linear operator defined as

\[
T_{ik,jk} = P_{T_i} (e_{ik} e_{jk}^*) \otimes (P_U - P_{U_l}) (e_{ik} e_{jk}^*),
\]

Then we have

\[
P_{T_i} P_{\Omega} (P_U - P_{U_l}) = \sum_{k=1}^{m} T_{ik,jk},
\]

\[
T'_{ik,jk} = (P_U - P_{U_l}) (e_{ik} e_{jk}^*) \otimes P_{T_i} (e_{ik} e_{jk}^*),
\]

\[
E [T_{ik,jk}] = \frac{1}{n^2} P_{T_i} (P_U - P_{U_l}),
\]

\[
E [T'_{ik,jk}] = \frac{1}{n^2} (P_U - P_{U_l}) P_{T_i}.
\]

Moreover,

\[
\| T_{ik,jk} \| \leq \| (P_U - P_{U_l}) (e_{ik} e_{jk}^*) \|_F \| P_{T_i} (e_{ik} e_{jk}^*) \|_F
\]

\[
\leq \left( \| P_U (e_{ik} e_{jk}^*) \|_F + \| P_{U_l} (e_{ik} e_{jk}^*) \|_F \right) \| P_{T_i} (e_{ik} e_{jk}^*) \|_F
\]

\[
\leq \frac{4 \mu r}{n},
\]

where the last inequality follows from

\[
\| P_U (e_{ik} e_{jk}^*) \|_F = \| P_U (e_{ik}) e_{jk}^* \|_F \leq \frac{\sqrt{\mu r}}{n},
\]

\[
\| P_{U_l} (e_{ik} e_{jk}^*) \|_F = \| P_{U_l} (e_{ik}) e_{jk}^* \|_F \leq \frac{\sqrt{\mu r}}{n},
\]

and

\[
\| P_{T_i} (e_{ik} e_{jk}^*) \|_F^2 = \langle P_{T_i} (e_{ik} e_{jk}^*), e_{ik} e_{jk}^* \rangle
\]

\[
= \langle P_{U_l} (e_{ik}) e_{jk}^* + e_{ik} (P_V (e_{jk})^* - P_{U_l} (e_{ik}) (P_V (e_{jk})^*), e_{ik} e_{jk}^* \rangle
\]

\[
= \| P_{U_l} (e_{ik}) \|^2 + \| P_V (e_{jk}) \|^2 - \| P_{U_l} (e_{ik}) \|^2 \| P_V (e_{jk}) \|^2
\]

\[
\leq \frac{2 \mu r}{n}.
\]

So

\[
\| T_{ik,jk} - E [T_{ik,jk}] \| \leq \| T_{ik,jk} \| + \| E [T_{ik,jk}] \| \leq \frac{4 \mu r}{n} + \frac{2}{n^2} \leq \frac{5 \mu r}{n}.
\]
To apply the Bernstein inequality, we also need to bound
\[
\| \mathbb{E} \left[ (T_{ik,jk} - \mathbb{E}(T_{ik,jk}))^* (T_{ik,jk} - \mathbb{E}(T_{ik,jk})) \right] \|
\]
and
\[
\| \mathbb{E} \left[ (T_{ik,jk} - \mathbb{E}(T_{ik,jk})) (T_{ik,jk} - \mathbb{E}(T_{ik,jk}))^* \right] \|.
\]
The first one can be proceeded as follows
\[
\| \mathbb{E} \left[ (T_{ik,jk} - \mathbb{E}(T_{ik,jk}))^* (T_{ik,jk} - \mathbb{E}(T_{ik,jk})) \right] \|
= \| \mathbb{E} \left[ T_{ik,jk}^* T_{ik,jk} \right] - \mathbb{E} \left[ T_{ik,jk}^* \right] \mathbb{E} \left[ T_{ik,jk} \right] \|
\leq \| \mathbb{E} \left[ T_{ik,jk}^* T_{ik,jk} \right] \| + \left\| \frac{1}{n^4} (P_U - P_{U_1}) P_{T_1} (P_U - P_{U_1}) \right\|
\leq \| \mathbb{E} \left[ (P_{U_1} - (e_{ik} e_{jk}^*) \otimes (P_U - P_{U_1}) (e_{ik} e_{jk}^*) \right] \| + \frac{4}{n^4}
\leq \frac{2 \mu r}{n} \| (P_U - P_{U_1}) (e_{ik} e_{jk}^*) \otimes (P_U - P_{U_1}) (e_{ik} e_{jk}^*) \| + \frac{4}{n^4}
\leq \frac{2 \mu r}{n} \frac{1}{n^2} \| (P_U - P_{U_1})^2 \| + \frac{4}{n^4}
\leq \frac{9 \mu r}{n^3},
\]
where the first inequality follows from (39) and (40), the third inequality follows from (43), and the fourth inequality follows from the fact
\[
\mathbb{E} \left[ (P_U - P_{U_1}) (e_{ik} e_{jk}^*) \otimes (P_U - P_{U_1}) (e_{ik} e_{jk}^*) \right] = \frac{1}{n^2} (P_U - P_{U_1})^2.
\]

Similarly, we have
\[
\| \mathbb{E} \left[ (T_{ik,jk} - \mathbb{E}(T_{ik,jk})) (T_{ik,jk} - \mathbb{E}(T_{ik,jk}))^* \right] \|
= \| \mathbb{E} \left[ T_{ik,jk} T_{ik,jk}^* \right] - \mathbb{E} \left[ T_{ik,jk}^* \right] \mathbb{E} \left[ T_{ik,jk} \right] \|
\leq \| \mathbb{E} \left[ T_{ik,jk} T_{ik,jk}^* \right] \| + \left\| \frac{1}{n^4} (P_U - P_{U_1})^2 P_{T_1} \right\|
\leq \| \mathbb{E} \left[ (P_{U_1} - (e_{ik} e_{jk}^*) \otimes P_{T_1} (e_{ik} e_{jk}^*) \right] \| + \frac{4}{n^4}
\leq \frac{4 \mu r}{n} \| (P_{U_1} - (e_{ik} e_{jk}^*) \otimes P_{T_1} (e_{ik} e_{jk}^*) \| + \frac{4}{n^4}
\leq \frac{4 \mu r}{n} \frac{1}{n^2} \| P_{T_1} \| + \frac{4}{n^4}
\leq \frac{9 \mu r}{n^3},
\]
where the first inequality follows from (39) and (40), the third inequality follows from (41) and (42), and the fourth inequality follows from the fact
\[
\mathbb{E} \left[ P_{T_1} (e_{ik} e_{jk}^*) \otimes P_{T_1} (e_{ik} e_{jk}^*) \right] = \frac{1}{n^2} P_{T_1}.
\]
Finally, the theorem follows by applying Thm. A.1 to (37) with the bounds (44), (45) and (46).
B.4 Proof of Lemma 4.4

By the assumption, (19) is valid for \( l = 0 \). Assume it is valid for \( j \leq l \). Then

\[
c_{l+1} \leq \rho_1 c_l + \rho_2 \sum_{j=0}^{l-1} \gamma^{l-j} c_j
\]

\[
\leq \rho_1 \nu^l c_0 + \rho_2 \sum_{j=0}^{l-1} \gamma^{l-j} \nu^j c_0
\]

\[
= \nu^l c_0 \left( \rho_1 + \rho_2 \sum_{j=0}^{l-1} \left( \frac{\gamma}{\nu} \right)^{l-j} \right)
\]

\[
\leq \nu^l c_0 \left( \rho_1 + \frac{\rho_2 \gamma}{1 - \gamma/\nu} \right)
\]

\[
= \nu^l c_0 \left( \rho_1 + \frac{\rho_2 \gamma}{\nu - \gamma} \right).
\]

So it suffices to show that \( \rho_1 + \frac{\rho_2 \gamma}{\nu - \gamma} = \nu \). It is equivalent to show that

\[
\nu^2 - (\rho_1 + \gamma) \nu - (\rho_2 - \rho_1) \gamma = 0.
\]

which is true since

\[
\nu = \frac{1}{2} \left( \tau_1 + \sqrt{\tau_1^2 + 4\tau_2} \right)
\]

with \( \tau_1 = \rho_1 + \gamma \) and \( \tau_2 = (\rho_2 - \rho_1) \gamma \).

B.5 Proof of Lemma 4.5

Since

\[
\|U_l - UQ\|_F^2 = 2r - 2 \langle U_l, UQ \rangle,
\]

\[
\|U_l U_l^* - U U^*\|_F^2 = 2r - 2 \langle U_l U_l^*, U U^* \rangle,
\]

it suffices to show that there exist a \( Q \) such that

\[
\langle U_l, UQ \rangle \geq \langle U_l U_l^*, U U^* \rangle.
\]

It is equivalent to show that

\[
\langle U^* U_l, Q \rangle \geq \langle U^* U_l, U^* U_l \rangle
\]

for some unitary matrix \( Q \in \mathbb{R}^{r \times r} \). Let \( U_l^* U_l = Q_1 \Lambda Q_2^* \) be the singular value decomposition of \( U_l^* U_l \). Then we have \( \Lambda(i,i) \leq 1 \) (1 \( i \leq r \)), and we can choose \( Q = Q_1 Q_2^* \).