

A. Supplement

In this section, we provide the missing proofs.

A.1. Proof of Theorem 2

Proof. An important aspect of the assumptions is that the space of atoms spanned by \mathbf{S} is orthogonal to the span of \mathbf{L} . Furthermore, $\text{span}(\mathbf{L} \cup \mathbf{S}) \supset \text{span}(\mathbf{S})$. Let $k = k + r$. We will first upper bound the denominator in the submodularity ratio. From strong concavity,

$$\frac{m_{\bar{k}}}{2} \|\mathbf{B}^{(\text{LUS})} - \mathbf{B}^{(\text{L})}\|_F^2 \leq \ell(\mathbf{B}^{(\text{L})}) - \ell(\mathbf{B}^{(\text{LUS})}) + \langle \nabla \ell(\mathbf{B}^{(\text{L})}), \mathbf{B}^{(\text{LUS})} - \mathbf{B}^{(\text{L})} \rangle$$

Rearranging

$$\begin{aligned} 0 \leq \ell(\mathbf{B}^{(\text{LUS})}) - \ell(\mathbf{B}^{(\text{L})}) &\leq \langle \nabla \ell(\mathbf{B}^{(\text{L})}), \mathbf{B}^{(\text{LUS})} - \mathbf{B}^{(\text{L})} \rangle - \frac{m_{\bar{k}}}{2} \|\mathbf{B}^{(\text{LUS})} - \mathbf{B}^{(\text{L})}\|_F^2 \\ &\leq \arg \max_{\substack{\mathbf{X}: \\ \mathbf{X} = \mathbf{U}_{\text{LUS}} \mathbf{H} \mathbf{V}_{\text{LUS}} \\ \mathbf{H} \in \mathbb{R}^{|\text{LUS}| \times |\text{LUS}|}} \langle \nabla \ell(\mathbf{B}^{(\text{L})}), \mathbf{X} - \mathbf{B}^{(\text{L})} \rangle - \frac{m_{\bar{k}}}{2} \|\mathbf{X} - \mathbf{B}^{(\text{L})}\|_F^2 \\ &= \arg \max_{\substack{\mathbf{X}: \\ \mathbf{X} = \mathbf{U}_{\text{LUS}} \mathbf{H} \mathbf{V}_{\text{LUS}} \\ \mathbf{H} \in \mathbb{R}^{|\text{LUS}| \times |\text{LUS}|}} \langle P_{\mathbf{U}_S}(\nabla \ell(\mathbf{B}^{(\text{L})})) P_{\mathbf{V}_S}, \mathbf{X} - \mathbf{B}^{(\text{L})} \rangle - \frac{m_{\bar{k}}}{2} \|\mathbf{X} - \mathbf{B}^{(\text{L})}\|_F^2, \end{aligned}$$

where the last equality holds because $\langle \nabla \ell(\mathbf{B}^{(\text{L})}), P_{\mathbf{U}_L} \mathbf{X} P_{\mathbf{V}_L} - \mathbf{B}^{(\text{L})} \rangle = 0$. Solving the argmax problem, we get $\mathbf{X} = \mathbf{B}^{(\text{L})} + \frac{1}{m_{\bar{k}}} P_{\mathbf{U}_S}(\nabla \ell(\mathbf{B}^{(\text{L})})) P_{\mathbf{V}_S}$. Plugging in, we get,

$$\ell(\mathbf{B}^{(\text{LUS})}) - \ell(\mathbf{B}^{(\text{L})}) \leq \frac{1}{2m_{\bar{k}}} \|P_{\mathbf{U}_S}(\nabla \ell(\mathbf{B}^{(\text{L})})) P_{\mathbf{V}_S}\|_F^2$$

We next bound the numerator. Recall that the atoms in \mathbf{S} are orthogonal to each other *i.e.* \mathbf{U}_S and \mathbf{V}_S are both orthonormal.

For clarity, we define the shorthand, $\mathbf{B}_{ij}^{(\text{LUS})} = \langle \mathbf{u}_i \mathbf{v}_j^\top, \mathbf{B}^{(\text{LUS})} \rangle \mathbf{u}_i \mathbf{v}_j^\top$, for $i, j \in [|\mathbf{L} \cup \mathbf{S}|]$.

With an arbitrary $i \in \mathbf{S}$, and arbitrary scalars $\alpha_{ii}, \alpha_{ij}, \alpha_{ji}$ for $j \in \mathbf{L}$,

$$\begin{aligned} \ell(\mathbf{B}^{(\text{LU}\{i\})}) - \ell(\mathbf{B}^{(\text{L})}) &\geq \ell(\mathbf{B}^{(\text{L})} + \alpha_{ii} \mathbf{B}_{ii}^{(\text{LUS})} + \sum_{j \in \mathbf{L}} \alpha_{ij} \mathbf{B}_{ij}^{(\text{LUS})} + \sum_{j \in \mathbf{L}} \alpha_{ji} \mathbf{B}_{ji}^{(\text{LUS})}) - \ell(\mathbf{B}^{(\text{L})}) \\ &\geq \langle \nabla \ell(\mathbf{B}^{(\text{L})}), \alpha_{ii} \mathbf{B}_{ii}^{(\text{LUS})} + \sum_{j \in \mathbf{L}} \alpha_{ij} \mathbf{B}_{ij}^{(\text{LUS})} + \sum_{j \in \mathbf{L}} \alpha_{ji} \mathbf{B}_{ji}^{(\text{LUS})} \rangle \\ &\quad - \frac{\tilde{M}_1}{2} \left[\alpha_{ii}^2 \|\mathbf{B}_{ii}^{(\text{LUS})}\|_F^2 + \sum_{j \in \mathbf{L}} \alpha_{ij}^2 \|\mathbf{B}_{ij}^{(\text{LUS})}\|_F^2 + \sum_{j \in \mathbf{L}} \alpha_{ji}^2 \|\mathbf{B}_{ji}^{(\text{LUS})}\|_F^2 \right]. \\ &\geq \frac{\langle \nabla \ell(\mathbf{B}^{(\text{L})}), \mathbf{B}_{ii}^{(\text{LUS})} \rangle^2}{2\tilde{M}_1 \|\mathbf{B}_{ii}^{(\text{LUS})}\|_F^2} + \sum_{j \in \mathbf{L}} \left(\frac{\langle \nabla \ell(\mathbf{B}^{(\text{L})}), \mathbf{B}_{ij}^{(\text{LUS})} \rangle^2}{2\tilde{M}_1 \|\mathbf{B}_{ij}^{(\text{LUS})}\|_F^2} + \frac{\langle \nabla \ell(\mathbf{B}^{(\text{L})}), \mathbf{B}_{ji}^{(\text{LUS})} \rangle^2}{2\tilde{M}_1 \|\mathbf{B}_{ji}^{(\text{LUS})}\|_F^2} \right), \end{aligned}$$

where the last inequality follows by setting $\alpha_{ij} = \frac{\langle \nabla \ell(\mathbf{B}^{(\text{L})}), \mathbf{B}_{ij}^{(\text{LUS})} \rangle}{\tilde{M}_1 \|\mathbf{B}_{ij}^{(\text{LUS})}\|_F^2}$ for $j \in \mathbf{L}$, and for $j = i$.

Summing up for all $i \in \mathbf{S}$, we get

$$\begin{aligned} \sum_{i \in S} \ell(\mathbf{B}^{(\mathcal{L} \cup \{i\})}) - \ell(\mathbf{B}^{(\mathcal{L})}) &\geq \sum_{i \in S} \left[\frac{\langle \nabla \ell(\mathbf{B}^{(\mathcal{L})}), \mathbf{B}_{ii}^{(\text{LUS})} \rangle^2}{2\tilde{M}_1 \|\mathbf{B}_{ii}^{(\text{LUS})}\|_F^2} + \sum_{j \in \mathcal{L}} \left(\frac{\langle \nabla \ell(\mathbf{B}^{(\mathcal{L})}), \mathbf{B}_{ij}^{(\text{LUS})} \rangle^2}{2\tilde{M}_1 \|\mathbf{B}_{ij}^{(\text{LUS})}\|_F^2} + \frac{\langle \nabla \ell(\mathbf{B}^{(\mathcal{L})}), \mathbf{B}_{ji}^{(\text{LUS})} \rangle^2}{2\tilde{M}_1 \|\mathbf{B}_{ji}^{(\text{LUS})}\|_F^2} \right) \right] \\ &= \frac{1}{2\tilde{M}_1} \|P_{\mathcal{U}_S} \nabla \ell(\mathbf{B}^{(\mathcal{L})}) P_{\mathcal{V}_S}\|_F^2 \end{aligned}$$

□

A.2. Proofs for greedy improvement

Let S_i^G be the support set formed by Algorithm 1 at iteration i . Define $A(i) := f(S_i^G) - f(S_{i-1}^G)$ with $A(0) = 0$ as the greedy improvement. We also define $B(i) := f(S^*) - f(S_i^G)$ to be the remaining amount to improve, where S^* is the optimum k -sized solution. We provide an auxiliary Lemma that uses the submodularity ratio to lower bound the greedy improvement in terms of best possible improvement from step i .

Lemma 1. *At iteration i , the incremental gain of the greedy method (Algorithm 1) is*

$$A(i+1) \geq \frac{\tau \gamma_{S_i^G, r}}{r} B(i).$$

Proof. Let $S = S_i^G$. Let S^R be the sequential orthogonalization of the atoms in S^* relative to S . Thus,

$$\begin{aligned} rA(i+1) &\geq |S^R|A(i+1) \geq \tau |S^R| \max_{a \in S^R} f(S \cup \{a\}) - f(S) \\ &\geq \tau \sum_{a \in S^R} [f(S \cup \{a\}) - f(S)] \\ &\geq \tau \gamma_{S, |S^R|} [f(S \cup S^R) - f(S)] \\ &\geq \tau \gamma_{S, |S^R|} B(i) \end{aligned}$$

Note that the last inequality follows because $f(S \cup S^R) \geq f(S^*)$. The penultimate inequality follows by the definition of weak submodularity, which applies in this case because the atoms in S^R are orthogonal to each other and are also orthogonal to S . □

Using Lemma 1, one can prove an approximation guarantee for Algorithm 1.

A.2.1. PROOF OF THEOREM 3

Proof. From the notation used for Lemma 1, $A(i+1) = B(i) - B(i+1)$. Let $C = \frac{\tau \gamma_{S_i^G, r}}{r}$. From Lemma 1, we have,

$$B(i+1) \leq (1-C)B(i) \leq (1-C)^{i+1}B(0).$$

From its definition, $B(0) = f(S^*) - f(\emptyset)$. So we get,

$$\begin{aligned} [f(S^*) - f(\emptyset)] - [f(S_i^G) - f(\emptyset)] &\leq (1-C)^i [f(S^*) - f(\emptyset)] \\ \implies [f(S_i^G) - f(\emptyset)] &\geq (1 - (1-C)^i) [f(S^*) - f(\emptyset)] \geq \left(1 - \frac{1}{e^{\frac{1}{\tau \gamma_{S_i^G, r} \frac{k}{r}}}}\right) [f(S^*) - f(\emptyset)] \end{aligned}$$

from which the result follows. □

A.3. Proof for GECO bounds

Let S_i^O be the support set selected by the GECO procedure (Algorithm 2) at iteration i . Similar to the section on greedy improvement, we define some notation. Let $D(i) := f(S_i^O) - f(S_{i-1}^O)$ be the improvement made at step i , and as before we have $B(i) = f(S^*) - f(S_i^O)$ be the remaining amount to improve.

We prove the following auxiliary lemma which lower bounds the gain after adding the atom selected by the subroutine `OMPSe1` in terms of operator norm of the gradient of the current iterate and smoothness of the function.

Lemma 2. *Assume that $\ell(\cdot)$ is m_i -strongly concave and M_i -smooth over matrices of in the set $\tilde{\Omega} := \{(\mathbf{X}, \mathbf{Y}) : \text{rank}(\mathbf{X} - \mathbf{Y}) \leq 1\}$. Then,*

$$D(i+1) \geq \frac{\tau m_{r+k}}{r\tilde{M}_1} B(i).$$

Proof. For simplicity, say $L = S_i^O$. Recall that for a given support set L , $f(L) = \ell(\mathbf{B}^{(L)})$ i.e. we denote by $\mathbf{B}^{(L)}$ the argmax for $\ell(\cdot)$ for a given support set L . Hence, by the optimality of $\mathbf{B}^{(L \cup \{i\})}$,

$$\begin{aligned} D(i+1) &= \ell(\mathbf{B}^{(L \cup \{i\})}) - \ell(\mathbf{B}^{(L)}) \\ &\geq \ell(\mathbf{B}^{(L)} + \alpha \mathbf{u} \mathbf{v}^\top) - \ell(\mathbf{B}^{(L)}) \end{aligned}$$

for an arbitrary $\alpha \in \mathbb{R}$, and the vectors \mathbf{u}, \mathbf{v} selected by `OMPSe1`. Using the smoothness of the $\ell(\cdot)$, we get,

$$D(i+1) \geq \alpha \langle \nabla \ell(\mathbf{B}^{(L)}), \mathbf{u} \mathbf{v}^\top \rangle - \alpha^2 \frac{\tilde{M}_1}{2}$$

Putting in $\alpha = \frac{\tau}{\tilde{M}_1} \|\nabla \ell(\mathbf{B}^{(L)})\|_2$, and by τ -optimality of `OMPSe1`, we get,

$$D(i+1) \geq \frac{\tau^2}{2\tilde{M}_1} \|\nabla \ell(\mathbf{B}^{(L)})\|_2^2$$

Let S^R be obtained from after sequentially orthogonalizing S^* w.r.t. S_i . By definition of the operator norm, we further get,

$$\begin{aligned} D(i+1) &\geq \frac{\tau^2}{2\tilde{M}_1} \|\nabla \ell(\mathbf{B}^{(L)})\|_2^2 \\ &\geq \frac{\tau^2}{2r\tilde{M}_1} \sum_{i \in S^R} \langle \mathbf{u}_i \mathbf{v}_i^\top, \nabla \ell(\mathbf{B}^{(L)}) \rangle^2 \\ &= \|P_{\mathbf{U}_{S^R}} \nabla \ell(\mathbf{B}^{(L)}) P_{\mathbf{V}_{S^R}}\|_F^2 \\ &\geq \frac{\tau^2 m_{r+k}}{r\tilde{M}_1} \left(\ell(\mathbf{B}^{(L \cup S^R)}) - \ell(\mathbf{B}^{(L)}) \right) \\ &\geq \frac{\tau^2 m_{r+k}}{r\tilde{M}_1} \left(\ell(\mathbf{B}^{S^*}) - \ell(\mathbf{B}^{(L)}) \right) \\ &= \frac{\tau^2 m_{r+k}}{r\tilde{M}_1} B(i) \end{aligned}$$

□

The proof for Theorem 4 from Lemma 2 now follows using the same steps as for Theorem 3 from Lemma 2.

A.4. Proof for recovery bounds

A.4.1. PROOF OF THEOREM 5

For clarity of representation, let $C = C_{r,k}$, and for an arbitrary $\mathbf{H} \in \mathbb{R}^{r \times r}$, let $\mathbf{B}_r = \mathbf{U}_S^\top \mathbf{H} \mathbf{V}_S$, and $\Delta := \mathbf{B}^{(S_r)} - \mathbf{B}_S$. Note that Δ has rank at most $(k+r)$. Recall that by the m_{k+r} RSC (Definition 3),

$$\ell(\mathbf{B}^{(S_k)}) - \ell(\mathbf{B}_r) - \langle \nabla \ell(\mathbf{B}_r), \Delta \rangle \leq \frac{-m_{k+r}}{2} \|\Delta\|_F^2.$$

From the approximation guarantee, we have,

$$\begin{aligned} \ell(\mathbf{B}^{(S_k)}) - \ell(\mathbf{B}_r) &\geq (1-C)[\ell(\mathbf{0}) - \ell(\mathbf{B}_r)] \\ \implies \ell(\mathbf{B}^{(S_k)}) - \ell(\mathbf{B}_r) - \langle \nabla \ell(\mathbf{B}_r), \Delta \rangle &\geq (1-C)[\ell(\mathbf{0}) - \ell(\mathbf{B}_r)] - \langle \nabla \ell(\mathbf{B}_r), \Delta \rangle \\ \implies \frac{-m_{k+r}}{2} \|\Delta\|_F^2 &\geq (1-C)[\ell(\mathbf{0}) - \ell(\mathbf{B}_r)] - \langle \nabla \ell(\mathbf{B}_r), \Delta \rangle \\ &\geq (1-C)[\ell(\mathbf{0}) - \ell(\mathbf{B}_r)] - (k+r)^{1/2} \|\nabla \ell(\mathbf{B}_r)\|_2 \|\Delta\|_F, \end{aligned}$$

where the last inequality is due to generalized Holder's inequality. Using $2ab \leq ca^2 + \frac{b^2}{c}$ for any positive numbers a, b, c , we get

$$\frac{m_{k+r}}{2} \|\Delta\|_F^2 \leq (k+r) \frac{\|\nabla \ell(\mathbf{B}_r)\|_2^2}{m_{k+r}} + \frac{m_{k+r} \|\Delta\|_F^2}{4} + (1-C)[\ell(\mathbf{B}_r) - \ell(\mathbf{0})],$$

which completes the proof.