

Appendices

A COST-BENEFIT GREEDY

Algorithm 1 Cost-benefit greedy

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1:  $U \leftarrow [d], S \leftarrow \emptyset$ 
2: while  $U \neq \emptyset$  do
3:    $j \leftarrow \operatorname{argmax}_{j' \in U} \frac{F(j'|S)}{G(j'|S)}$ 
4:   if  $G(S \cup \{j\}) \leq c$  then
5:      $S \leftarrow S \cup \{j\}$ 
6:    $U \leftarrow U \setminus \{j\}$ 
7: return  $S$ 
    
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We prove the approximation guarantee of the CBG algorithm (Algorithm 1) for the following problem:

$$\underset{S \subseteq [d]}{\text{maximize}} F(S) \quad \text{subject to } G(S) \leq c.$$

To obtain the main theorem, we use the following definitions and lemmas.

Let S^* be any subset of $[d]$ such that $G(S^*) \leq c^*$ and $|S^*| = k^*$. As in the theorem of the main paper, we assume that $\min\{c, c^*\} \geq \rho$ holds. We suppose that $t + 1$ elements are added when $G(S) > c - \rho$ occurs in the loops of Algorithm 1 for the first time. We let j_i be the i -th element added to S for $i \in [t + 1]$. We define $S_i := \{j_1, \dots, j_i\}$ for $i \in [t + 1]$ and $S_0 := \emptyset$. Thanks to the monotonicity of $G(\cdot)$, the definition of ρ , and $G(S_t) \leq c - \rho$, we have

$$G(S_i) = G(S_{i-1}) + G(j_i | S_{i-1}) \leq G(S_t) + G(j_i | S_{i-1}) \leq c - \rho + \rho = c$$

for $i \in [t + 1]$; in particular, we have $c - \rho \leq G(S_{t+1}) \leq c$. Namely, $G(S_1), \dots, G(S_{t+1})$ do not exceed the budget value, which means that j_i ($i \in [t + 1]$) is the element added in the i -th iteration of the algorithm. Moreover, the output, S , satisfies $S_{t+1} \subseteq S$.

Lemma 1. For $i = 1, \dots, t + 1$, we have

$$F(S_i) - F(S_{i-1}) \geq \theta \beta_{k^*} \gamma_{S_t, k^*} \cdot \frac{G(j_i | S_{i-1})}{c^*} (F(S^*) - F(S_{i-1})).$$

Proof. Thanks to the weak submodularity of $F(\cdot)$, we have

$$\begin{aligned} \sum_{j \in S^* \setminus S_{i-1}} F(j | S_{i-1}) &\geq \gamma_{S_{i-1}, k^*} F(S^* \setminus S_{i-1} | S_{i-1}) \\ &= \gamma_{S_{i-1}, k^*} F(S^* | S_{i-1}) \geq \gamma_{S_t, k^*} F(S^* | S_{i-1}). \end{aligned}$$

Since j_i is chosen greedily, $j_i = \operatorname{argmax}_{j \notin S_{i-1}} \frac{F(j|S_{i-1})}{G(j|S_{i-1})}$ holds, and hence $\frac{F(j_i|S_{i-1})}{G(j_i|S_{i-1})} \geq \frac{F(j|S_{i-1})}{G(j|S_{i-1})}$ for any $j \in S^* \setminus S_{i-1}$. Using this fact and the above inequality, we obtain

$$\begin{aligned} F(j_i | S_{i-1}) \sum_{j \in S^* \setminus S_{i-1}} G(j | S_{i-1}) &\geq G(j_i | S_{i-1}) \sum_{j \in S^* \setminus S_{i-1}} F(j | S_{i-1}) \\ &\geq G(j_i | S_{i-1}) \times \gamma_{S_t, k^*} F(S^* | S_{i-1}). \end{aligned}$$

We consider bounding from above $\sum_{j \in S^* \setminus S_{i-1}} G(j | S_{i-1})$ in LHS. By using the definition of restricted inverse curvature and superadditivity ratio of $G(\cdot)$, we obtain

$$\sum_{j \in S^* \setminus S_{i-1}} G(j | S_{i-1}) \leq \frac{1}{\theta} \sum_{j \in S^* \setminus S_{i-1}} G(j) \leq \frac{1}{\theta \beta_{k^*}} G(S^* \setminus S_{i-1}) \leq \frac{c^*}{\theta \beta_{k^*}},$$

where the last inequality comes from $G(\mathbf{S}^* \setminus \mathbf{S}_{i-1}) \leq G(\mathbf{S}^*) \leq c^*$. Hence we obtain

$$\frac{c^*}{\theta\beta_{k^*}}(F(\mathbf{S}_i) - F(\mathbf{S}_{i-1})) = \frac{c^*}{\theta\beta_{k^*}}F(j_i | \mathbf{S}_{i-1}) \geq G(j_i | \mathbf{S}_{i-1}) \times \gamma_{\mathbf{S}_i, k^*} F(\mathbf{S}^* | \mathbf{S}_{i-1}).$$

The lemma is obtained by using $F(\mathbf{S}^* | \mathbf{S}_{i-1}) = F(\mathbf{S}^* \cup \mathbf{S}_{i-1}) - F(\mathbf{S}_{i-1}) \geq F(\mathbf{S}^*) - F(\mathbf{S}_{i-1})$ and rearranging terms. \square

Lemma 2. For $i = 1, \dots, t+1$, we have

$$F(\mathbf{S}_i) \geq \left(1 - \prod_{i'=1}^i \left(1 - \theta\beta_{k^*}\gamma_{\mathbf{S}_{i'}, k^*} \cdot \frac{G(j_{i'} | \mathbf{S}_{i'-1})}{c^*}\right)\right) F(\mathbf{S}^*).$$

Proof. We prove the lemma by induction on $i = 1, \dots, t+1$. First, if $i = 1$, the target inequality holds thanks to Lemma 1. We then assume that the target inequality holds for $\mathbf{S}_1, \dots, \mathbf{S}_{i-1}$ and prove it for \mathbf{S}_i . Combining Lemma 1 and the assumption, we obtain

$$\begin{aligned} F(\mathbf{S}_i) &= F(\mathbf{S}_{i-1}) + (F(\mathbf{S}_i) - F(\mathbf{S}_{i-1})) \\ &\geq F(\mathbf{S}_{i-1}) + \theta\beta_{k^*}\gamma_{\mathbf{S}_i, k^*} \cdot \frac{G(j_i | \mathbf{S}_{i-1})}{c^*} (F(\mathbf{S}^*) - F(\mathbf{S}_{i-1})) \\ &= \left(1 - \theta\beta_{k^*}\gamma_{\mathbf{S}_i, k^*} \cdot \frac{G(j_i | \mathbf{S}_{i-1})}{c^*}\right) F(\mathbf{S}_{i-1}) + \theta\beta_{k^*}\gamma_{\mathbf{S}_i, k^*} \cdot \frac{G(j_i | \mathbf{S}_{i-1})}{c^*} F(\mathbf{S}^*) \\ &\geq \left(1 - \prod_{i'=1}^i \left(1 - \theta\beta_{k^*}\gamma_{\mathbf{S}_{i'}, k^*} \cdot \frac{G(j_{i'} | \mathbf{S}_{i'-1})}{c^*}\right)\right) F(\mathbf{S}^*). \end{aligned}$$

Thus the lemma holds by induction. \square

Theorem 1. Let \mathbf{S} be the output of CBG and \mathbf{S}^* be any subset that satisfies $G(\mathbf{S}^*) \leq c^*$ and $|\mathbf{S}^*| = k^*$. If $F(\cdot)$ has submodularity ratio $\gamma_{\mathbf{S}, k^*}$, $G(\cdot)$ has superadditivity ratio β_{k^*} and restricted inverse curvature θ , and $\min\{c, c^*\} \geq \rho$ holds, then we have

$$F(\mathbf{S}) \geq \left(1 - \exp\left(-\theta\beta_{k^*}\gamma_{\mathbf{S}, k^*} \cdot \frac{c - \rho}{c^*}\right)\right) F(\mathbf{S}^*).$$

Proof. We define $x := \theta\beta_{k^*}\gamma_{\mathbf{S}_i, k^*} \cdot \frac{c - \rho}{c^*}$ and $y_i := \frac{G(j_i | \mathbf{S}_{i-1})}{G(\mathbf{S}_{t+1})}$ for $i \in [t+1]$. Thanks to $G(\mathbf{S}_{t+1}) \geq c - \rho$, $G(j_i | \mathbf{S}_{i-1}) \leq \rho \leq c^*$, and $\theta\beta_{k^*}\gamma_{\mathbf{S}_i, k^*} \leq 1$, we obtain

$$xy_i = \theta\beta_{k^*}\gamma_{\mathbf{S}_i, k^*} \cdot \frac{c - \rho}{c^*} \cdot y_i \leq \theta\beta_{k^*}\gamma_{\mathbf{S}_i, k^*} \cdot \frac{G(\mathbf{S}_{t+1})}{G(j_i | \mathbf{S}_{i-1})} \cdot y_i = \theta\beta_{k^*}\gamma_{\mathbf{S}_i, k^*} \leq 1.$$

Hence $1 - xy_i \geq 0$. Since $\sum_{i=1}^{t+1} y_i = \sum_{i=1}^{t+1} \frac{G(j_i | \mathbf{S}_{i-1})}{G(\mathbf{S}_{t+1})} = 1$ holds, $\prod_{i=1}^{t+1} (1 - xy_i)$ attains its maximum value when we have $y_1 = \dots = y_{t+1} = \frac{1}{t+1}$. Thus we obtain

$$\prod_{i=1}^{t+1} \left(1 - \theta\beta_{k^*}\gamma_{\mathbf{S}_i, k^*} \cdot \frac{c - \rho}{c^*} \cdot \frac{G(j_i | \mathbf{S}_{i-1})}{G(\mathbf{S}_{t+1})}\right) \leq \left(1 - \theta\beta_{k^*}\gamma_{\mathbf{S}_i, k^*} \cdot \frac{c - \rho}{c^*} \cdot \frac{1}{t+1}\right)^{t+1}. \quad (\text{A1})$$

By using Lemma 2, inequality (A1), and $G(\mathbf{S}_{t+1}) \geq c - \rho$, we obtain

$$\begin{aligned}
 F(\mathbf{S}_{t+1}) &\geq \left(1 - \prod_{i=1}^{t+1} \left(1 - \theta\beta_{k^*}\gamma_{\mathbf{S}_t, k^*} \cdot \frac{G(j_i | \mathbf{S}_{i-1})}{c^*}\right)\right) F(\mathbf{S}^*) && \because \text{Lemma 2} \\
 &= \left(1 - \prod_{i=1}^{t+1} \left(1 - \theta\beta_{k^*}\gamma_{\mathbf{S}_t, k^*} \cdot \frac{c - \rho}{c^*} \cdot \frac{G(j_i | \mathbf{S}_{i-1})}{c - \rho}\right)\right) F(\mathbf{S}^*) \\
 &\geq \left(1 - \prod_{i=1}^{t+1} \left(1 - \theta\beta_{k^*}\gamma_{\mathbf{S}_t, k^*} \cdot \frac{c - \rho}{c^*} \cdot \frac{G(j_i | \mathbf{S}_{i-1})}{G(\mathbf{S}_{t+1})}\right)\right) F(\mathbf{S}^*) && \because G(\mathbf{S}_{t+1}) \geq c - \rho \\
 &\geq \left(1 - \left(1 - \theta\beta_{k^*}\gamma_{\mathbf{S}_t, k^*} \cdot \frac{c - \rho}{c^*} \cdot \frac{1}{t+1}\right)^{t+1}\right) F(\mathbf{S}^*) && \because \text{inequality (A1)} \\
 &\geq \left(1 - \exp\left(-\theta\beta_{k^*}\gamma_{\mathbf{S}_t, k^*} \cdot \frac{c - \rho}{c^*}\right)\right) F(\mathbf{S}^*).
 \end{aligned}$$

Since we have $\mathbf{S}_t \subseteq \mathbf{S}_{t+1} \subseteq \mathbf{S}$, we obtain

$$F(\mathbf{S}) \geq F(\mathbf{S}_{t+1}) \geq \left(1 - \exp\left(-\theta\beta_{k^*}\gamma_{\mathbf{S}, k^*} \cdot \frac{c - \rho}{c^*}\right)\right) F(\mathbf{S}^*).$$

□

B IHT WITH CBG PROJECTION

Algorithm 2 IHT with CBG projection

- 1: Initialize $\mathbf{x}_0 \in \mathbb{R}^{[d]}$
 - 2: **for** $t = 0, 1, \dots, T - 1$ **do**
 - 3: $\mathbf{g}_t \leftarrow \mathbf{x}_t - \eta \nabla l(\mathbf{x}_t)$
 - 4: $\mathbf{x}_{t+1} \leftarrow \mathcal{P}_c(\mathbf{g}_t)$ ▷ CBG projection
 - 5: **return** \mathbf{x}_T
-

We prove the theorem that guarantees the performance of Algorithm 2 for the following problem:

$$\underset{\mathbf{x} \in \mathbb{R}^d}{\text{minimize}} \quad l(\mathbf{x}) \quad \text{subject to} \quad G(\text{supp}(\mathbf{x})) \leq c.$$

We first explain the CBG projection (Step 4) in detail. Given any $\mathbf{z} \in \mathbb{R}^{[d]}$, $\hat{\mathbf{z}} = \mathcal{P}_c(\mathbf{z})$ is obtained as follows: We perform Algorithm 1 with objective function $F(\mathbf{S}) := \|\mathbf{z}_{\mathbf{S}}\|_2^2 = \sum_{j \in \mathbf{S}} |\mathbf{z}_j|^2$, cost function $G(\mathbf{S})$, and budget value c ; the resulting solution, \mathbf{S} , satisfies $c - \rho \leq G(\mathbf{S}) \leq c$. We set $\hat{\mathbf{z}}_j$ to \mathbf{z}_j if $j \in \mathbf{S}$ and 0 otherwise. Note that $F(\cdot)$ is monotone and modular, which implies that its submodularity ratio is equal to 1. We first prove a key lemma that guarantees the performance of the CBG projection.

Lemma 3. *Assume $c^* \geq \rho$ and let \mathbf{S}^* be an arbitrary subset such that $G(\mathbf{S}^*) \leq c^*$ and $|\mathbf{S}^*| = k^*$. Given any $\mathbf{z} \in \mathbb{R}^{[d]}$, we let $\mathbf{S} := \text{supp}(\mathcal{P}_c(\mathbf{z}))$. If $G(\cdot)$ has superadditivity ratio β_{k^*} and restricted inverse curvature θ , then the following inequality holds for any $\tilde{c} \geq \frac{c^*}{\theta\beta_{k^*}} \log(\|\mathbf{z}_{\mathbf{S}^*}\|_2^2/\epsilon) + \rho$ and $c > \tilde{c} + \rho$:*

$$\frac{\|\mathbf{z}_{\mathbf{S}^* \setminus \mathbf{S}}\|_2^2}{c^*} \leq \frac{\|\mathbf{z}_{\mathbf{S} \setminus \mathbf{S}^*}\|_2^2 + \epsilon}{\theta\beta_{k^*}(c - \tilde{c} - \rho)}.$$

Proof. We define $\tilde{\mathbf{S}}$ as the first subset, \mathbf{S} , in the loops of Algorithm 1 that satisfy $G(\mathbf{S}) > \tilde{c} - \rho$; note that $\tilde{c} - \rho < G(\tilde{\mathbf{S}}) \leq \tilde{c}$ holds. As in the proof of Theorem 1, we have

$$F(\tilde{\mathbf{S}}) \geq \left(1 - \exp\left(-\theta\beta_{k^*} \cdot \frac{\tilde{c} - \rho}{c^*}\right)\right) F(\mathbf{S}^*).$$

Therefore, from $\tilde{c} \geq \frac{c^*}{\theta\beta_{k^*}} \log(\|\mathbf{z}_{S^*}\|_2^2/\epsilon) + \rho = \frac{c^*}{\theta\beta_{k^*}} \log(F(S^*)/\epsilon) + \rho$, we obtain

$$F(\tilde{S}) \geq F(S^*) - \epsilon. \quad (\text{A2})$$

We then suppose that $t+1$ elements are added to \tilde{S} in the loops of Algorithm 1 when $G(S) > c - \rho$ occurs for the first time. We let j_i be the i -th element added to \tilde{S} . We define $\hat{S}_i := \{j_1, \dots, j_i\}$ for $i \in [t+1]$ and $\hat{S}_0 := \emptyset$. As discussed in the proof of Theorem 1, we have

$$\tilde{c} - \rho \leq G(\hat{S}_0 \cup \tilde{S}) \leq \dots \leq G(\hat{S}_{t+1} \cup \tilde{S}) = G(\hat{S}_t \cup \tilde{S}) + G(j_{t+1} \mid \hat{S}_t \cup \tilde{S}) \leq c - \rho + \rho = c.$$

This inequality means that the budget constraint is not violated for $i \in [t+1]$, and thus j_i is added in the $(|\tilde{S}| + i)$ -th iteration of Algorithm 1. In particular, we have $c - \rho \leq G(\hat{S}_{t+1} \cup \tilde{S}) \leq c$. Furthermore, the output, S , satisfies $\hat{S}_i \cup \tilde{S} \subseteq S$ for $i = 0, \dots, t+1$. Since j_i is chosen greedily w.r.t. the cost-benefit ratio, we have $\frac{F(j_i \mid \hat{S}_{i-1} \cup \tilde{S})}{G(j_i \mid \hat{S}_{i-1} \cup \tilde{S})} \geq \frac{F(j \mid \hat{S}_{i-1} \cup \tilde{S})}{G(j \mid \hat{S}_{i-1} \cup \tilde{S})}$ for any $j \in S^* \setminus \{\hat{S}_{i-1} \cup \tilde{S}\}$. Therefore, we obtain

$$F(j_i \mid \hat{S}_{i-1} \cup \tilde{S}) \sum_{j \in S^* \setminus \{\hat{S}_{i-1} \cup \tilde{S}\}} G(j \mid \hat{S}_{i-1} \cup \tilde{S}) \geq G(j_i \mid \hat{S}_{i-1} \cup \tilde{S}) \sum_{j \in S^* \setminus \{\hat{S}_{i-1} \cup \tilde{S}\}} F(j \mid \hat{S}_{i-1} \cup \tilde{S}). \quad (\text{A3})$$

We can bound from below $\sum_{j \in S^* \setminus \{\hat{S}_{i-1} \cup \tilde{S}\}} F(j \mid \hat{S}_{i-1} \cup \tilde{S})$ in RHS as follows

$$\sum_{j \in S^* \setminus \{\hat{S}_{i-1} \cup \tilde{S}\}} F(j \mid \hat{S}_{i-1} \cup \tilde{S}) = \sum_{j \in S^* \setminus \{\hat{S}_{i-1} \cup \tilde{S}\}} |\mathbf{z}_j|^2 \geq \|\mathbf{z}_{S^* \setminus S}\|_2^2.$$

On the other hand, $\sum_{j \in S^* \setminus \{\hat{S}_{i-1} \cup \tilde{S}\}} G(j \mid \hat{S}_{i-1} \cup \tilde{S})$ in LHS of (A3) can be bounded from above as follows:

$$\begin{aligned} & \sum_{j \in S^* \setminus \{\hat{S}_{i-1} \cup \tilde{S}\}} G(j \mid \hat{S}_{i-1} \cup \tilde{S}) \\ & \leq \frac{1}{\theta} \sum_{j \in S^* \setminus \{\hat{S}_{i-1} \cup \tilde{S}\}} G(j) \quad \because \text{definition of restricted inverse curvature} \\ & \leq \frac{1}{\theta\beta_{k^*}} G(S^* \setminus \{\hat{S}_{i-1} \cup \tilde{S}\}) \quad \because \text{definition of superadditivity ratio} \\ & \leq \frac{c^*}{\theta\beta_{k^*}}. \quad \because G(S^* \setminus \{\hat{S}_{i-1} \cup \tilde{S}\}) \leq c^* \end{aligned}$$

Consequently, we have

$$\begin{aligned} F(\hat{S}_i \cup \tilde{S}) - F(\hat{S}_{i-1} \cup \tilde{S}) &= F(j_i \mid \hat{S}_{i-1} \cup \tilde{S}) \\ &\geq \theta\beta_{k^*} \cdot \frac{G(j_i \mid \hat{S}_{i-1} \cup \tilde{S})}{c^*} \|\mathbf{z}_{S^* \setminus S}\|_2^2 = \theta\beta_{k^*} \cdot \frac{G(\hat{S}_i \cup \tilde{S}) - G(\hat{S}_{i-1} \cup \tilde{S})}{c^*} \|\mathbf{z}_{S^* \setminus S}\|_2^2. \end{aligned}$$

Taking the summation of both sides for $i = 1, \dots, t+1$, and using $G(\hat{S}_{t+1} \cup \tilde{S}) - G(\tilde{S}) \geq (c - \rho) - \tilde{c}$ and $\hat{S}_{t+1} \cup \tilde{S} \subseteq S$, we obtain

$$\begin{aligned} F(S) - F(\tilde{S}) &\geq F(\hat{S}_{t+1} \cup \tilde{S}) - F(\tilde{S}) \\ &\geq \theta\beta_{k^*} \cdot \frac{G(\hat{S}_{t+1} \cup \tilde{S}) - G(\tilde{S})}{c^*} \|\mathbf{z}_{S^* \setminus S}\|_2^2 \geq \theta\beta_{k^*} \cdot \frac{c - \tilde{c} - \rho}{c^*} \|\mathbf{z}_{S^* \setminus S}\|_2^2. \end{aligned} \quad (\text{A4})$$

Combining inequalities (A2) and (A4), we obtain the target inequality as follows:

$$\frac{\|\mathbf{z}_{S^* \setminus S}\|_2^2}{c^*} \leq \frac{F(S) - F(\tilde{S})}{\theta\beta_{k^*}(c - \tilde{c} - \rho)} \leq \frac{F(S) - F(S^*) + \epsilon}{\theta\beta_{k^*}(c - \tilde{c} - \rho)} \leq \frac{\|\mathbf{z}_{S \setminus S^*}\|_2^2 + \epsilon}{\theta\beta_{k^*}(c - \tilde{c} - \rho)},$$

where the last inequality comes from $F(S) - F(S^*) \leq F(S \cup S^*) - F(S^*) = \|\mathbf{z}_{S \setminus S^*}\|_2^2$. \square

Using the above lemma, we obtain the main theorem:

Theorem 2. Let $k := \max_{t:0 \leq t \leq T} \|\mathbf{x}_t\|_0$ and $\omega := \max_{t:0 \leq t \leq T} \|\mathbf{g}_t\|_2$. Assume that $l(\cdot)$ is continuously twice differentiable, μ_{2k+k^*} -RSC, and ν_{2k+k^*} -RSM, and that $G(\cdot)$ has superadditivity ratio β_{k^*} and restricted inverse curvature θ . Set $\eta = \frac{1}{\nu_{2k+k^*}}$. If $c^* \geq \rho$ and $c \geq \frac{4c^*}{\theta\beta_{k^*}} \left(\frac{\nu_{2k+k^*}}{\mu_{2k+k^*}} \right)^2 + \frac{2c^*}{\theta\beta_{k^*}} \log\left(\frac{\omega}{2\epsilon}\right) + 2\rho$ hold, then we have

$$\|\mathbf{x}_{t+1} - \mathbf{x}^*\|_2 \leq \left(1 - \frac{1}{2} \cdot \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}}\right) \|\mathbf{x}_t - \mathbf{x}^*\|_2 + \zeta + \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}} \cdot \epsilon,$$

where $\zeta := \frac{1}{\nu_{2k+k^*}} \left(1 + \frac{1}{2} \cdot \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}}\right) \max_{S \in \mathcal{F}} \|\nabla l(\mathbf{x}^*)_S\|_2$. Specifically, after

$$T \geq 2 \cdot \frac{\nu_{2k+k^*}}{\mu_{2k+k^*}} \log \frac{\|\mathbf{x}_0 - \mathbf{x}^*\|_2}{\epsilon}$$

steps, we have

$$\|\mathbf{x}_T - \mathbf{x}^*\|_2 \leq 3\epsilon + 2\zeta \cdot \frac{\nu_{2k+k^*}}{\mu_{2k+k^*}}.$$

Proof. Let $S^* := \text{supp}(\mathbf{x}^*)$, $S_t := \text{supp}(\mathbf{x}_t)$, $S_{t+1} := \text{supp}(\mathbf{x}_{t+1})$, and $U := S_{t+1} \cup S^*$. In what follows, given any $A, B \subseteq [d]$, if the inequality of RSC holds with $\Omega = \{(\mathbf{x}, \mathbf{y}) \mid \text{supp}(\mathbf{x}) \subseteq A, \text{supp}(\mathbf{y}) \subseteq B\}$, then we say $l(\cdot)$ is $\mu_{A,B}$ -RSC.

We first prove an inequality for later use. Note that $l(\cdot)$ is assumed to be twice differentiable. We let $\mathbf{H}(\mathbf{x})$ denote the Hessian of $l(\cdot)$ evaluated at \mathbf{x} . Given $A, B \subseteq [d]$ such that $A \subseteq B$, if $l(\cdot)$ is $\mu_{A,B}$ -RSC, then the inequality of RSC implies that function $l(\mathbf{x}) - \frac{\mu_{A,B}}{2} \|\mathbf{x}\|_2^2$ is convex at \mathbf{x} w.r.t. direction \mathbf{d} , where $\text{supp}(\mathbf{x}) \subseteq A$ and $\text{supp}(\mathbf{d}) \subseteq B$; i.e., $\mathbf{H}(\mathbf{x})_{B,B} \succeq \mu_{A,B} \mathbf{I}_{B,B}$ holds. This fact means that, for any $\mathbf{y} \in \mathbb{R}^{[d]}$ such that $\text{supp}(\mathbf{y}) \subseteq S^* \cup S_t$, the spectral norm of $(\mathbf{I} - \eta \mathbf{H}(\mathbf{y}))_{(U \cup S_t), (U \cup S_t)}$ is bounded from above by $1 - \eta \mu_{(S^* \cup S_t), (U \cup S_t)}$. Therefore, by using the mean value inequality, we obtain

$$\begin{aligned} \|(\mathbf{x}^* - \mathbf{x}_t - \eta(\nabla l(\mathbf{x}^*) - \nabla l(\mathbf{x}_t)))_U\|_2 &\leq \|(\mathbf{x}^* - \mathbf{x}_t - \eta(\nabla l(\mathbf{x}^*) - \nabla l(\mathbf{x}_t)))_{U \cup S_t}\|_2 \\ &\leq (1 - \eta \mu_{(S^* \cup S_t), (U \cup S_t)}) \|(\mathbf{x}_t - \mathbf{x}^*)\|_2 \\ &\leq (1 - \eta \mu_{2k+k^*}) \|(\mathbf{x}_t - \mathbf{x}^*)\|_2 \\ &= \left(1 - \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}}\right) \|(\mathbf{x}_t - \mathbf{x}^*)\|_2. \end{aligned} \quad (\text{A5})$$

We then evaluate the performance of the CBG projection by bounding $\|(\mathbf{x}_{t+1} - \mathbf{g}_t)_U\|_2^2$ from above. Since $\mathbf{x}_{t+1} = \mathcal{P}_c(\mathbf{g}_t)$, we have $\|(\mathbf{x}_{t+1} - \mathbf{g}_t)_U\|_2^2 = \|(\mathbf{g}_t)_{S^* \setminus S_{t+1}}\|_2^2$. From Lemma 3 with $\mathbf{z} = \mathbf{g}_t$, $S^* = \text{supp}(\mathbf{x}^*)$, $S = S_{t+1}$, and $\tilde{c} = \frac{2c^*}{\theta\beta_{k^*}} \log\left(\frac{\omega}{2\epsilon}\right) + \rho \geq \frac{c^*}{\theta\beta_{k^*}} \log\left(\frac{\|\mathbf{g}_t\|_2^2}{4\epsilon^2}\right) + \rho$, the following inequality holds for $c > \tilde{c} + \rho$:

$$\begin{aligned} \|(\mathbf{x}_{t+1} - \mathbf{g}_t)_U\|_2^2 &= \|(\mathbf{g}_t)_{S^* \setminus S_{t+1}}\|_2^2 \leq \frac{c^*}{\theta\beta_{k^*}(c - \tilde{c} - \rho)} \|(\mathbf{g}_t)_{S_{t+1} \setminus S^*}\|_2^2 + \frac{4c^*\epsilon^2}{\theta\beta_{k^*}(c - \tilde{c} - \rho)} \\ &\leq \frac{c^*}{\theta\beta_{k^*}(c - \tilde{c} - \rho)} (\|(\mathbf{g}_t)_{S_{t+1} \setminus S^*}\|_2^2 + \|(\mathbf{x}^* - \mathbf{g}_t)_{S^*}\|_2^2) + \frac{4c^*\epsilon^2}{\theta\beta_{k^*}(c - \tilde{c} - \rho)} \\ &= \frac{c^*}{\theta\beta_{k^*}(c - \tilde{c} - \rho)} \|(\mathbf{x}^* - \mathbf{g}_t)_U\|_2^2 + \frac{4c^*\epsilon^2}{\theta\beta_{k^*}(c - \tilde{c} - \rho)}. \end{aligned} \quad (\text{A6})$$

Setting $c \geq \frac{4c^*}{\theta\beta_{k^*}} \left(\frac{\nu_{2k+k^*}}{\mu_{2k+k^*}} \right)^2 + \frac{2c^*}{\theta\beta_{k^*}} \log\left(\frac{\omega}{2\epsilon}\right) + 2\rho = \frac{4c^*}{\theta\beta_{k^*}} \left(\frac{\nu_{2k+k^*}}{\mu_{2k+k^*}} \right)^2 + \tilde{c} + \rho$, we obtain the target inequality as

follows:

$$\begin{aligned}
 & \|\mathbf{x}_{t+1} - \mathbf{x}^*\|_2 \\
 = & \|(\mathbf{x}_{t+1} - \mathbf{x}^*)_{\mathcal{U}}\|_2 && \because \text{supp}(\mathbf{x}_{t+1} - \mathbf{x}^*) \subseteq \mathcal{U} \\
 \leq & \|(\mathbf{x}_{t+1} - \mathbf{g}_t)_{\mathcal{U}}\|_2 + \|(\mathbf{x}^* - \mathbf{g}_t)_{\mathcal{U}}\|_2 && \because \text{triangle inequality} \\
 \leq & \left(1 + \sqrt{\frac{c^*}{\theta\beta_{k^*}(c - \tilde{c} - \rho)}}\right) \|(\mathbf{x}^* - \mathbf{g}_t)_{\mathcal{U}}\|_2 + 2\epsilon\sqrt{\frac{c^*}{\theta\beta_{k^*}(c - \tilde{c} - \rho)}} && \because \text{(A6) and } \sqrt{x^2 + y^2} \leq |x| + |y| \\
 \leq & \left(1 + \frac{1}{2} \cdot \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}}\right) \|(\mathbf{x}^* - \mathbf{x}_t + \eta\nabla l(\mathbf{x}_t))_{\mathcal{U}}\|_2 + \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}} \cdot \epsilon && \because \text{definitions of } c \text{ and } \mathbf{g}_t \\
 \leq & \left(1 + \frac{1}{2} \cdot \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}}\right) \|(\mathbf{x}^* - \mathbf{x}_t - \eta(\nabla l(\mathbf{x}^*) - \nabla l(\mathbf{x}_t)))_{\mathcal{U}}\|_2 \\
 & + \eta \left(1 + \frac{1}{2} \cdot \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}}\right) \|\nabla l(\mathbf{x}^*)_{\mathcal{S}_{t+1}}\|_2 + \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}} \cdot \epsilon && \because \text{triangle inequality and } \nabla l(\mathbf{x}^*)_{\mathcal{S}^*} = 0 \\
 \leq & \left(1 + \frac{1}{2} \cdot \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}}\right) \|(\mathbf{x}^* - \mathbf{x}_t - \eta(\nabla l(\mathbf{x}^*) - \nabla l(\mathbf{x}_t)))_{\mathcal{U}}\|_2 + \zeta + \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}} \cdot \epsilon && \because \text{definition of } \zeta \\
 \leq & \left(1 + \frac{1}{2} \cdot \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}}\right) \left(1 - \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}}\right) \|\mathbf{x}_t - \mathbf{x}^*\|_2 + \zeta + \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}} \cdot \epsilon && \because \text{(A5)} \\
 \leq & \left(1 - \frac{1}{2} \cdot \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}}\right) \|\mathbf{x}_t - \mathbf{x}^*\|_2 + \zeta + \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}} \cdot \epsilon. && \because \left(1 + \frac{a}{2}\right)(1 - a) \leq 1 - \frac{a}{2} \text{ for } a \geq 0
 \end{aligned}$$

We turn to the inequality obtained after T steps. Using the inequality proved above, we obtain

$$\begin{aligned}
 & \|\mathbf{x}_T - \mathbf{x}^*\|_2 \\
 \leq & \left(1 - \frac{1}{2} \cdot \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}}\right)^T \|\mathbf{x}_0 - \mathbf{x}^*\|_2 + \left(\zeta + \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}} \cdot \epsilon\right) \sum_{t=0}^{T-1} \left(1 - \frac{1}{2} \cdot \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}}\right)^t \\
 \leq & \left(1 - \frac{1}{2} \cdot \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}}\right)^T \|\mathbf{x}_0 - \mathbf{x}^*\|_2 + 2\zeta \cdot \frac{\nu_{2k+k^*}}{\mu_{2k+k^*}} + 2\epsilon.
 \end{aligned}$$

Setting $T \geq 2 \cdot \frac{\nu_{2k+k^*}}{\mu_{2k+k^*}} \log \frac{\|\mathbf{x}_0 - \mathbf{x}^*\|_2}{\epsilon} \geq \log \frac{\|\mathbf{x}_0 - \mathbf{x}^*\|_2}{\epsilon} / \log \left(1 - \frac{1}{2} \cdot \frac{\mu_{2k+k^*}}{\nu_{2k+k^*}}\right)^{-1}$, we obtain

$$\|\mathbf{x}_T - \mathbf{x}^*\|_2 \leq 3\epsilon + 2\zeta \cdot \frac{\nu_{2k+k^*}}{\mu_{2k+k^*}}.$$

□