

A. Technical Lemmas

The following lemma is a characterization of the co-coercivity of the objective function $F(\mathbf{x})$. A similar result was obtained in [Nguyen et al. \(2014, Corollary 8\)](#) but we present a refined analysis which is essential for our purpose.

Lemma 9. *For a given support set Ω , assume that the continuous function $F(\mathbf{x})$ is $M_{|\Omega|}$ -RSS and is m_K -RSC for some sparsity level K . Then, for all vectors \mathbf{w} and \mathbf{w}' with $|\text{supp}(\mathbf{w} - \mathbf{w}') \cup \Omega| \leq K$, we have*

$$\|\nabla_{\Omega} F(\mathbf{w}') - \nabla_{\Omega} F(\mathbf{w})\|^2 \leq 2M_{|\Omega|}(F(\mathbf{w}') - F(\mathbf{w}) - \langle \nabla F(\mathbf{w}), \mathbf{w}' - \mathbf{w} \rangle).$$

Proof. We define an auxiliary function

$$G(\mathbf{x}) \stackrel{\text{def}}{=} F(\mathbf{x}) - \langle \nabla F(\mathbf{w}), \mathbf{x} \rangle.$$

For all vectors \mathbf{x} and \mathbf{y} , we have

$$\|\nabla G(\mathbf{x}) - \nabla G(\mathbf{y})\| = \|\nabla F(\mathbf{x}) - \nabla F(\mathbf{y})\| \leq M_{|\text{supp}(\mathbf{x}-\mathbf{y})|} \|\mathbf{x} - \mathbf{y}\|,$$

which is equivalent to

$$G(\mathbf{x}) - G(\mathbf{y}) - \langle \nabla G(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle \leq \frac{M_r}{2} \|\mathbf{x} - \mathbf{y}\|^2, \quad (7)$$

where $r = |\text{supp}(\mathbf{x} - \mathbf{y})|$. On the other hand, due to the RSC property of $F(\mathbf{x})$, we obtain

$$G(\mathbf{x}) - G(\mathbf{w}) = F(\mathbf{x}) - F(\mathbf{w}) - \langle \nabla F(\mathbf{w}), \mathbf{x} - \mathbf{w} \rangle \geq \frac{m_{|\text{supp}(\mathbf{x}-\mathbf{w})|}}{2} \|\mathbf{x} - \mathbf{w}\|^2 \geq 0,$$

provided that $|\text{supp}(\mathbf{x} - \mathbf{w})| \leq K$. For the given support set Ω , we pick $\mathbf{x} = \mathbf{w}' - \frac{1}{M_{|\Omega|}} \nabla_{\Omega} G(\mathbf{w}')$. Clearly, for such a choice of \mathbf{x} , we have $\text{supp}(\mathbf{x} - \mathbf{w}) = \text{supp}(\mathbf{w} - \mathbf{w}') \cup \Omega$. Hence, by assuming that $|\text{supp}(\mathbf{w} - \mathbf{w}') \cup \Omega|$ is not larger than K , we get

$$\begin{aligned} G(\mathbf{w}) &\leq G\left(\mathbf{w}' - \frac{1}{M_{|\Omega|}} \nabla_{\Omega} G(\mathbf{w}')\right) \\ &\stackrel{(7)}{\leq} G(\mathbf{w}') + \left\langle \nabla G(\mathbf{w}'), -\frac{1}{M_{|\Omega|}} \nabla_{\Omega} G(\mathbf{w}') \right\rangle + \frac{1}{2M_{|\Omega|}} \|\nabla_{\Omega} G(\mathbf{w}')\|^2 \\ &= G(\mathbf{w}') - \frac{1}{2M_{|\Omega|}} \|\nabla_{\Omega} G(\mathbf{w}')\|^2. \end{aligned}$$

Now expanding $\nabla_{\Omega} G(\mathbf{w}')$ and rearranging the terms give the desired result. \square

Lemma 10 (Lemma 1 in [Wang et al. \(2016\)](#)). *Let \mathbf{u} and \mathbf{z} be two distinct vectors and let $W = \text{supp}(\mathbf{u}) \cap \text{supp}(\mathbf{z})$. Also, let U be the support set of the top r (in magnitude) elements in \mathbf{u} . Then, the following holds for all $r \geq 1$:*

$$\langle \mathbf{u}, \mathbf{z} \rangle \leq \sqrt{\left\lceil \frac{|W|}{r} \right\rceil} \|\mathbf{u}_U\| \cdot \|\mathbf{z}_W\|.$$

Lemma 11. *Suppose that $F(\mathbf{x})$ is m_K -restricted strongly convex and M_K -restricted smooth for some sparsity level $K > 0$. Then for all $\eta > 0$, all vectors $\mathbf{x}, \mathbf{x}' \in \mathbb{R}^d$ and for any Hessian matrix \mathbf{H} of $F(\mathbf{x})$, we have*

$$|\langle \mathbf{x}, (\mathbf{I} - \eta \mathbf{H}) \mathbf{x}' \rangle| \leq \rho \|\mathbf{x}\| \cdot \|\mathbf{x}'\|, \quad \text{if } |\text{supp}(\mathbf{x}) \cup \text{supp}(\mathbf{x}')| \leq K,$$

and

$$\|((\mathbf{I} - \eta \mathbf{H}) \mathbf{x})_S\| \leq \rho \|\mathbf{x}\|, \quad \text{if } |S \cup \text{supp}(\mathbf{x})| \leq K,$$

where

$$\rho = \max \{ |\eta m_K - 1|, |\eta M_K - 1| \}.$$

Proof. Since \mathbf{H} is a Hessian matrix, we always have a decomposition $\mathbf{H} = \mathbf{A}^\top \mathbf{A}$ for some matrix \mathbf{A} . Denote $T = \text{supp}(\mathbf{x}) \cup \text{supp}(\mathbf{y})$. By simple algebra, we have

$$\begin{aligned} |\langle \mathbf{x}, (\mathbf{I} - \eta \mathbf{H}) \mathbf{x}' \rangle| &= |\langle \mathbf{x}, \mathbf{x}' \rangle - \eta \langle \mathbf{A} \mathbf{x}, \mathbf{A} \mathbf{x}' \rangle| \\ &\stackrel{\zeta_1}{\leq} |\langle \mathbf{x}, \mathbf{x}' \rangle - \eta \langle \mathbf{A}_T \mathbf{x}, \mathbf{A}_T \mathbf{x}' \rangle| \\ &= \left| \left\langle \mathbf{x}, (\mathbf{I} - \eta \mathbf{A}_T^\top \mathbf{A}_T) \mathbf{x}' \right\rangle \right| \\ &\leq \left\| \mathbf{I} - \eta \mathbf{A}_T^\top \mathbf{A}_T \right\| \cdot \|\mathbf{x}\| \cdot \|\mathbf{x}'\| \\ &\stackrel{\zeta_2}{\leq} \max\{|\eta m_K - 1|, |\eta M_K - 1|\} \cdot \|\mathbf{x}\| \cdot \|\mathbf{x}'\|. \end{aligned}$$

Here, ζ_1 follows from the fact that $\text{supp}(\mathbf{x}) \cup \text{supp}(\mathbf{y}) = T$ and ζ_2 holds because the RSC and RSS properties imply that the singular values of any Hessian matrix restricted on an K -sparse support set are lower and upper bounded by m_K and M_K , respectively.

For some index set S subject to $|S \cup \text{supp}(\mathbf{x})| \leq K$, let $\mathbf{x}' = ((\mathbf{I} - \eta \mathbf{H}) \mathbf{x})_S$. We immediately obtain

$$\|\mathbf{x}'\|^2 = \langle \mathbf{x}', (\mathbf{I} - \eta \mathbf{H}) \mathbf{x} \rangle \leq \rho \|\mathbf{x}'\| \cdot \|\mathbf{x}\|,$$

indicating

$$\|((\mathbf{I} - \eta \mathbf{H}) \mathbf{x})_S\| \leq \rho \|\mathbf{x}\|.$$

□

Lemma 12. *Suppose that $F(\mathbf{x})$ is m_K -restricted strongly convex and M_K -restricted smooth for some sparsity level $K > 0$. For all $\eta > 0$, all vectors $\mathbf{x}, \mathbf{x}' \in \mathbb{R}^d$ and support set T such that $|\text{supp}(\mathbf{x} - \mathbf{x}') \cup T| \leq K$, the following holds:*

$$\|(\mathbf{x} - \mathbf{x}' - \eta \nabla F(\mathbf{x}) + \eta \nabla F(\mathbf{x}'))_T\| \leq \rho \|\mathbf{x} - \mathbf{x}'\|$$

where ρ is given in Lemma 11.

Proof. In fact, for any two vectors \mathbf{x} and \mathbf{x}' , there always exists a quantity $\theta \in [0, 1]$, such that

$$\nabla F(\mathbf{x}) - \nabla F(\mathbf{x}') = \nabla^2 F(\theta \mathbf{x} + (1 - \theta) \mathbf{x}') (\mathbf{x} - \mathbf{x}').$$

Let $\mathbf{H} = \nabla^2 F(\theta \mathbf{x} + (1 - \theta) \mathbf{x}')$. We write

$$\begin{aligned} \|(\mathbf{x} - \mathbf{x}' - \eta \nabla F(\mathbf{x}) + \eta \nabla F(\mathbf{x}'))_T\| &= \|(\mathbf{x} - \mathbf{x}' - \eta \mathbf{H}(\mathbf{x} - \mathbf{x}'))_T\| \\ &= \|((\mathbf{I} - \eta \mathbf{H})(\mathbf{x} - \mathbf{x}'))_T\| \\ &\leq \rho \|\mathbf{x} - \mathbf{x}'\|, \end{aligned}$$

where the last inequality applies Lemma 11. □

Lemma 13. *Suppose that \mathbf{x} is a k -sparse vector and let $\mathbf{b} = \mathbf{x} - \eta \nabla F(\mathbf{x})$. Let T be the support set that contains the k largest absolute values of \mathbf{b} . Assume that the function $F(\mathbf{x})$ is M_{2k} -restricted smooth, then we have the following:*

$$F(\mathbf{b}_T) \leq F(\mathbf{x}) - \frac{1 - \eta M_{2k}}{2\eta} \|\mathbf{b}_T - \mathbf{x}\|^2.$$

Proof. The RSS condition implies that

$$\begin{aligned} F(\mathbf{b}_T) - F(\mathbf{x}) &\leq \langle \nabla F(\mathbf{x}), \mathbf{b}_T - \mathbf{x} \rangle + \frac{M_{2k}}{2} \|\mathbf{b}_T - \mathbf{x}\|^2 \\ &\leq -\frac{1}{2\eta} \|\mathbf{b}_T - \mathbf{x}\|^2 + \frac{M_{2k}}{2} \|\mathbf{b}_T - \mathbf{x}\|^2, \end{aligned}$$

where the second inequality is due to the fact that

$$\begin{aligned}\|\mathbf{b}_T - \mathbf{b}\|^2 &= \|\mathbf{b}_T - \mathbf{x} + \eta \nabla F(\mathbf{x})\|^2 \\ &\leq \|\mathbf{x} - \mathbf{x} + \eta \nabla F(\mathbf{x})\|^2 \\ &= \|\eta \nabla F(\mathbf{x})\|^2,\end{aligned}$$

implying

$$2\eta \langle \nabla F(\mathbf{x}), \mathbf{b}_T - \mathbf{x} \rangle \leq -\|\mathbf{b}_T - \mathbf{x}\|^2.$$

□

Lemma 14. *Suppose that $F(\mathbf{x})$ is m_K -RSC. Then for any vectors \mathbf{x} and \mathbf{x}' with $\|\mathbf{x} - \mathbf{x}'\|_0 \leq K$, the following holds:*

$$\|\mathbf{x} - \mathbf{x}'\| \leq \sqrt{\frac{2 \max\{F(\mathbf{x}) - F(\mathbf{x}'), 0\}}{m_K}} + \frac{2 \|\nabla_T F(\mathbf{x}')\|}{m_K}$$

where $T = \text{supp}(\mathbf{x} - \mathbf{x}')$.

Proof. The RSC property immediately implies

$$\begin{aligned}F(\mathbf{x}) - F(\mathbf{x}') &\geq \langle \nabla F(\mathbf{x}'), \mathbf{x} - \mathbf{x}' \rangle + \frac{m_K}{2} \|\mathbf{x} - \mathbf{x}'\|^2 \\ &\geq -\|\nabla_T F(\mathbf{x}')\| \cdot \|\mathbf{x} - \mathbf{x}'\| + \frac{m_K}{2} \|\mathbf{x} - \mathbf{x}'\|^2.\end{aligned}$$

Discussing the sign of $F(\mathbf{x}) - F(\mathbf{x}')$ and solving the above quadratic inequality completes the proof. □

Lemma 15. *Assume that $F(\mathbf{x})$ is m_{k+s} -RSC and M_{2k} -RSS. Suppose that for all $t \geq 0$, \mathbf{x}^t is k -sparse and the following holds:*

$$F(\mathbf{x}^{t+1}) - F(\bar{\mathbf{x}}) \leq \mu (F(\mathbf{x}^t) - F(\bar{\mathbf{x}})) + \tau,$$

where $0 < \mu < 1$, $\tau \geq 0$ and $\bar{\mathbf{x}}$ is an arbitrary s -sparse signal. Then,

$$\|\mathbf{x}^t - \bar{\mathbf{x}}\| \leq \sqrt{\frac{2M}{m}} (\sqrt{\mu})^t \|\mathbf{x}^0 - \bar{\mathbf{x}}\| + \frac{3}{m} \|\nabla_{k+s} F(\bar{\mathbf{x}})\| + \sqrt{\frac{2\tau}{m(1-\mu)}}.$$

Proof. The RSS property implies that

$$\begin{aligned}F(\mathbf{x}^0) - F(\bar{\mathbf{x}}) &\leq \langle \nabla F(\bar{\mathbf{x}}), \mathbf{x}^0 - \bar{\mathbf{x}} \rangle + \frac{M}{2} \|\mathbf{x}^0 - \bar{\mathbf{x}}\|^2 \\ &\leq \frac{M}{2} \|\mathbf{x}^0 - \bar{\mathbf{x}}\|^2 + \frac{1}{2M} \|\nabla_{k+s} F(\bar{\mathbf{x}})\|^2 + \frac{M}{2} \|\mathbf{x}^0 - \bar{\mathbf{x}}\|^2 \\ &\leq M \|\mathbf{x}^0 - \bar{\mathbf{x}}\|^2 + \frac{1}{2M} \|\nabla_{k+s} F(\bar{\mathbf{x}})\|^2.\end{aligned}$$

Hence,

$$F(\mathbf{x}^t) - F(\bar{\mathbf{x}}) \leq \mu^t M \|\mathbf{x}^0 - \bar{\mathbf{x}}\|^2 + \frac{1}{2M} \|\nabla_{k+s} F(\bar{\mathbf{x}})\|^2 + \frac{\tau}{1-\mu}.$$

By Lemma 14, we have

$$\begin{aligned}
 \|\mathbf{x}^t - \bar{\mathbf{x}}\| &\leq \sqrt{\frac{2}{m}} \sqrt{\mu^t M \|\mathbf{x}^0 - \bar{\mathbf{x}}\|^2 + \frac{\|\nabla_{k+s} F(\bar{\mathbf{x}})\|^2}{2M}} + \frac{\tau}{1-\mu} + \frac{2}{m} \|\nabla_{k+s} F(\bar{\mathbf{x}})\| \\
 &\leq \sqrt{\frac{2M}{m}} (\sqrt{\mu})^t \|\mathbf{x}^0 - \bar{\mathbf{x}}\| + \sqrt{\frac{1}{mM}} \|\nabla_{k+s} F(\bar{\mathbf{x}})\| \\
 &\quad + \frac{2}{m} \|\nabla_{k+s} F(\bar{\mathbf{x}})\| + \sqrt{\frac{2\tau}{m(1-\mu)}} \\
 &\leq \sqrt{\frac{2M}{m}} (\sqrt{\mu})^t \|\mathbf{x}^0 - \bar{\mathbf{x}}\| + \frac{3}{m} \|\nabla_{k+s} F(\bar{\mathbf{x}})\| + \sqrt{\frac{2\tau}{m(1-\mu)}}.
 \end{aligned}$$

□

Lemma 16. Let $\bar{\mathbf{x}} \in \mathbb{R}^d$ be an s -sparse vector supported on S . For a k -sparse vector \mathbf{x} supported on Q with $k \geq s$, let $\mathbf{b} = \mathbf{x} - \eta \nabla F(\mathbf{x})$ and let $T = \text{supp}(\mathbf{b}, k)$. Suppose that the function $F(\mathbf{x})$ is m_{2k+s} -RSC and M_{2k+s} -RSS. Then we have

$$\|\bar{\mathbf{x}}_{S \setminus T}\| \leq \nu \rho \|\mathbf{x} - \bar{\mathbf{x}}\| + \nu \eta \|\nabla_{T \Delta S} F(\bar{\mathbf{x}})\|,$$

where $\nu = \sqrt{1 + s/k}$ and ρ is given by Lemma 11.

Proof. We note the fact that the support sets $T \setminus S$ and $S \setminus T$ are disjoint. Moreover, the set $T \setminus S$ contains $|T \setminus S|$ number of top $|T|$ elements of \mathbf{b} . Hence, we have

$$\frac{1}{|T \setminus S|} \|\mathbf{b}_{T \setminus S}\|^2 \geq \frac{1}{|S \setminus T|} \|\mathbf{b}_{S \setminus T}\|^2. \quad (8)$$

That is,

$$\|\mathbf{b}_{T \setminus S}\| \geq \sqrt{\frac{|T \setminus S|}{|S \setminus T|}} \|\mathbf{b}_{S \setminus T}\| = \sqrt{\frac{k - |T \cap S|}{s - |T \cap S|}} \|\mathbf{b}_{S \setminus T}\| \geq \sqrt{\frac{k}{s}} \|\mathbf{b}_{S \setminus T}\|.$$

Note that the above holds also for $T = S$. Since $\bar{\mathbf{x}}$ is supported on S , the left hand side reads as

$$\|\mathbf{b}_{T \setminus S}\| = \left\| (\mathbf{x} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}))_{T \setminus S} \right\|,$$

while the right hand side reads as

$$\begin{aligned}
 \|\mathbf{b}_{S \setminus T}\| &= \left\| (\mathbf{x} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}))_{S \setminus T} + \bar{\mathbf{x}}_{S \setminus T} \right\| \\
 &\geq \|\bar{\mathbf{x}}_{S \setminus T}\| - \left\| (\mathbf{x} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}))_{S \setminus T} \right\|.
 \end{aligned}$$

Denote $\nu = \sqrt{1 + s/k}$. In this way, we arrive at

$$\begin{aligned}
 \|\bar{\mathbf{x}}_{S \setminus T}\| &\leq \sqrt{\frac{s}{k}} \left(\left\| (\mathbf{x} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}))_{T \setminus S} \right\| + \left\| (\mathbf{x} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}))_{S \setminus T} \right\| \right) \\
 &\leq \nu \left\| (\mathbf{x} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}))_{T \Delta S} \right\| \\
 &\leq \nu \left\| (\mathbf{x} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}) + \eta \nabla F(\bar{\mathbf{x}}))_{T \Delta S} \right\| + \nu \eta \|\nabla_{T \Delta S} F(\bar{\mathbf{x}})\| \\
 &\leq \nu \left\| (\mathbf{x} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}) + \eta \nabla F(\bar{\mathbf{x}}))_{T \cup Q \cup S} \right\| + \nu \eta \|\nabla_{T \Delta S} F(\bar{\mathbf{x}})\| \\
 &\leq \nu \rho_{2k+s} \|\mathbf{x} - \bar{\mathbf{x}}\| + \nu \eta \|\nabla_{T \Delta S} F(\bar{\mathbf{x}})\|,
 \end{aligned}$$

where the second inequality follows from the fact that $ax + by \leq \sqrt{a^2 + b^2} \sqrt{x^2 + y^2}$ and we applied Lemma 12 for the last inequality. □

Lemma 17. Consider the HTP algorithm with exact solutions. Assume (A1). Then

$$\|\nabla_{S^{t+1} \setminus S^t} F(\mathbf{x}^t)\|^2 \geq 2m\zeta (F(\mathbf{x}^t) - F(\bar{\mathbf{x}})),$$

where

$$\zeta = \frac{|S^{t+1} \setminus S^t|}{|S^{t+1} \setminus S^t| + |S \setminus S^t|}.$$

Proof. The lemma holds clearly for either $S^{t+1} = S^t$ or $F(\mathbf{x}^t) \leq F(\bar{\mathbf{x}})$. Hence, in the following we only prove the result by assuming $S^{t+1} \neq S^t$ and $F(\mathbf{x}^t) > F(\bar{\mathbf{x}})$. Due to the RSC property, we have

$$F(\bar{\mathbf{x}}) - F(\mathbf{x}^t) - \langle \nabla F(\mathbf{x}^t), \bar{\mathbf{x}} - \mathbf{x}^t \rangle \geq \frac{m_{k+s}}{2} \|\bar{\mathbf{x}} - \mathbf{x}^t\|^2,$$

which implies

$$\begin{aligned} \langle \nabla F(\mathbf{x}^t), -\bar{\mathbf{x}} \rangle &\geq \frac{m_{k+s}}{2} \|\bar{\mathbf{x}} - \mathbf{x}^t\|^2 + F(\mathbf{x}^t) - F(\bar{\mathbf{x}}) \\ &\geq \sqrt{2m_{k+s}} \|\bar{\mathbf{x}} - \mathbf{x}^t\| \sqrt{F(\mathbf{x}^t) - F(\bar{\mathbf{x}})}. \end{aligned}$$

By invoking Lemma 10 with $\mathbf{u} = \nabla F(\mathbf{x}^t)$ and $\mathbf{z} = -\bar{\mathbf{x}}$ therein, we have

$$\begin{aligned} \langle \nabla F(\mathbf{x}^t), -\bar{\mathbf{x}} \rangle &\leq \sqrt{\frac{|S \setminus S^t|}{|S^{t+1} \setminus S^t|} + 1} \|\nabla_{S^{t+1} \setminus S^t} F(\mathbf{x}^t)\| \cdot \|\bar{\mathbf{x}}_{S \setminus S^t}\| \\ &= \sqrt{\frac{|S \setminus S^t|}{|S^{t+1} \setminus S^t|} + 1} \|\nabla_{S^{t+1} \setminus S^t} F(\mathbf{x}^t)\| \cdot \|(\bar{\mathbf{x}} - \mathbf{x}^t)_{S \setminus S^t}\| \\ &\leq \sqrt{\frac{|S \setminus S^t|}{|S^{t+1} \setminus S^t|} + 1} \|\nabla_{S^{t+1} \setminus S^t} F(\mathbf{x}^t)\| \cdot \|\bar{\mathbf{x}} - \mathbf{x}^t\|. \end{aligned}$$

It is worth mentioning that the first inequality above holds because $\nabla F(\mathbf{x}^t)$ is supported on \bar{S}^t and $S^{t+1} \setminus S^t$ contains the $|S^{t+1} \setminus S^t|$ number of largest (in magnitude) elements of $\nabla F(\mathbf{x}^t)$. Therefore, we obtain the result. \square

B. Proofs for Section 2

B.1. Proof for Prop. 1

Proof. Due to the RSS property, we have

$$\begin{aligned} F(\mathbf{b}_{S^{t+1}}^{t+1}) - F(\mathbf{x}^t) &\leq \langle \nabla F(\mathbf{x}^t), \mathbf{b}_{S^{t+1}}^{t+1} - \mathbf{x}^t \rangle + \frac{M}{2} \|\mathbf{b}_{S^{t+1}}^{t+1} - \mathbf{x}^t\|^2 \\ &\stackrel{\zeta_1}{=} \langle \nabla_{S^{t+1} \setminus S^t} F(\mathbf{x}^t), \mathbf{b}_{S^{t+1} \setminus S^t}^{t+1} \rangle + \frac{M}{2} \left(\|\mathbf{b}_{S^{t+1} \setminus S^t}^{t+1}\|^2 \right. \\ &\quad \left. + \|\mathbf{b}_{S^{t+1} \cap S^t}^{t+1} - \mathbf{x}_{S^{t+1} \cap S^t}^t\|^2 + \|\mathbf{x}_{S^t \setminus S^{t+1}}^t\|^2 \right) \\ &\leq \langle \nabla_{S^{t+1} \setminus S^t} F(\mathbf{x}^t), \mathbf{b}_{S^{t+1} \setminus S^t}^{t+1} \rangle + M \|\mathbf{b}_{S^{t+1} \setminus S^t}^{t+1}\|^2 \\ &\stackrel{\zeta_3}{=} -\eta(1 - \eta M) \|\nabla_{S^{t+1} \setminus S^t} F(\mathbf{x}^t)\|^2. \end{aligned}$$

Above, we observe that $\nabla F(\mathbf{x}^t)$ is supported on \bar{S}^t and we simply decompose the support set $S^{t+1} \cup S^t$ into three mutually disjoint sets, and hence ζ_1 holds. To see why ζ_2 holds, we note that for any set $\Omega \subset S^t$, $\mathbf{b}_{\Omega}^{t+1} = \mathbf{x}_{\Omega}^t$. Hence, $\mathbf{b}_{S^{t+1} \cap S^t}^{t+1} = \mathbf{x}_{S^{t+1} \cap S^t}^t$. Moreover, since $\mathbf{x}_{S^t \setminus S^{t+1}}^t = \mathbf{b}_{S^t \setminus S^{t+1}}^{t+1}$ and any element in $\mathbf{b}_{S^t \setminus S^{t+1}}^{t+1}$ is not larger than that in $\mathbf{b}_{S^{t+1} \setminus S^t}^{t+1}$ (recall that S^{t+1} is obtained by hard thresholding), we have $\|\mathbf{x}_{S^t \setminus S^{t+1}}^t\| \leq \|\mathbf{b}_{S^{t+1} \setminus S^t}^{t+1}\|$ where we use the fact that $|S^t \setminus S^{t+1}| = |S^{t+1} \setminus S^t|$. Therefore, ζ_2 holds. Finally, we write $\mathbf{b}_{S^{t+1} \setminus S^t}^{t+1} = -\eta \nabla_{S^{t+1} \setminus S^t} F(\mathbf{x}^t)$ and obtain ζ_3 .

Since \mathbf{x}^{t+1} is a minimizer of $F(\mathbf{x})$ over the support set S^{t+1} , it immediately follows that

$$F(\mathbf{x}^{t+1}) - F(\mathbf{x}^t) \leq F(\mathbf{b}_{S^{t+1}}^{t+1}) - F(\mathbf{x}^t) \leq -\eta(1 - \eta M) \|\nabla_{S^{t+1} \setminus S^t} F(\mathbf{x}^t)\|^2.$$

Now we invoke Lemma 17 and pick $\eta \leq 1/M$,

$$F(\mathbf{x}^{t+1}) - F(\mathbf{x}^t) \leq \eta(\eta M - 1) \cdot \frac{2m}{1+s} (F(\mathbf{x}^t) - F(\bar{\mathbf{x}})),$$

which gives

$$F(\mathbf{x}^{t+1}) - F(\bar{\mathbf{x}}) \leq \beta (F(\mathbf{x}^t) - F(\bar{\mathbf{x}})),$$

where $\beta = 1 - \frac{2m\eta(1-\eta M)}{1+s}$. □

B.2. Proof for Prop. 2

Proof. This is a direct result by combining Prop. 1 and Lemma 15. □

B.3. Proof for Lemma 3

Proof. Let $\mathbf{x}_*^t = \arg \min_{\text{supp}(\mathbf{x}) \subset S^t} F(\mathbf{x})$. Since \mathbf{x}^t and \mathbf{x}_*^t are both supported on S^t , we apply Lemma 9 and obtain

$$\begin{aligned} \|\nabla_{S^t} F(\mathbf{x}^t)\|^2 &= \|\nabla_{S^t} F(\mathbf{x}^t) - \nabla_{S^t} F(\mathbf{x}_*^t)\|^2 \\ &\leq 2M (F(\mathbf{x}^t) - F(\mathbf{x}_*^t)) - \langle \nabla F(\mathbf{x}_*^t), \mathbf{x}^t - \mathbf{x}_*^t \rangle \\ &\leq 2M\epsilon. \end{aligned}$$

Above, the second inequality uses the fact that $\nabla_{S^t} F(\mathbf{x}_*^t) = 0$ and $F(\mathbf{x}^t) \leq F(\mathbf{x}_*^t) + \epsilon$. □

B.4. Proof for Prop. 4

Proof. We have by Lemma 16 that

$$\|\bar{\mathbf{x}}_{S^{t+1}}\| \leq \sqrt{2}\rho \|\mathbf{x}^t - \bar{\mathbf{x}}\| + \frac{2}{m} \|\nabla_{k+s} F(\bar{\mathbf{x}})\|,$$

where $\rho = 1 - \eta m$. On the other hand, Lemma 18 together with Lemma 3 shows that

$$\|\mathbf{x}^{t+1} - \bar{\mathbf{x}}\| \leq \kappa \|\bar{\mathbf{x}}_{S^{t+1}}\| + \frac{1}{m} \|\nabla_k F(\bar{\mathbf{x}})\| + \frac{1}{m} \sqrt{2M\epsilon}.$$

Therefore,

$$\|\mathbf{x}^{t+1} - \bar{\mathbf{x}}\| \leq \sqrt{2}\kappa\rho \|\mathbf{x}^t - \bar{\mathbf{x}}\| + \frac{3\kappa}{m} \|\nabla_{k+s} F(\bar{\mathbf{x}})\| + \frac{\sqrt{2M\epsilon}}{m}$$

We need to ensure

$$\sqrt{2}\kappa(1 - \eta m) < 1.$$

Let $\eta = \eta'/M$ with $\eta' < 1$. Then, the above holds provided that

$$\kappa < 1 + \frac{1}{\sqrt{2}} \text{ and } \eta' > \kappa - \frac{1}{\sqrt{2}}.$$

By induction and picking proper η' to make $\sqrt{2}\kappa(1 - \eta m) < \sqrt{2}/4$, we have

$$\|\mathbf{x}^t - \bar{\mathbf{x}}\| \leq (\sqrt{2}(\kappa - \eta'))^t \|\mathbf{x}^0 - \bar{\mathbf{x}}\| + \frac{6\kappa}{m} \|\nabla_{k+s} F(\bar{\mathbf{x}})\| + \frac{4\sqrt{M\epsilon}}{m}.$$

□

B.5. Proof for Prop. 5

Proof. Our proof in this part is inspired by Yuan et al. (2016). Let $\mathbf{x}_*^t = \arg \min_{\text{supp}(\mathbf{x}) \subset S^t} F(\mathbf{x})$. Then

$$\begin{aligned} F(\mathbf{x}^t) - F(\mathbf{x}^{t-1}) &\leq F(\mathbf{x}_*^t) - F(\mathbf{x}^{t-1}) + \epsilon \\ &\leq F(\mathbf{b}_{S^t}^t) - F(\mathbf{x}^{t-1}) + \epsilon \\ &\leq -\frac{1-\eta M}{2\eta} \|\mathbf{b}_{S^t}^t - \mathbf{x}^{t-1}\|^2 + \epsilon, \end{aligned}$$

where the last inequality follows from Lemma 13. Now we bound the term $\|\mathbf{b}_{S^t}^t - \mathbf{x}^{t-1}\|^2$. Note that \mathbf{x}^{t-1} is supported on S^{t-1} . Hence,

$$\begin{aligned} \|\mathbf{b}_{S^t}^t - \mathbf{x}^{t-1}\|^2 &= \|\mathbf{x}_{S^t \cap S^{t-1}}^{t-1} - \eta \nabla_{S^t} F(\mathbf{x}^{t-1}) - \mathbf{x}^{t-1}\|^2 \\ &= \|\mathbf{x}_{S^t \setminus S^{t-1}}^{t-1} - \eta \nabla_{S^t} F(\mathbf{x}^{t-1})\|^2 \\ &= \|\mathbf{x}_{S^t \setminus S^{t-1}}^{t-1}\|^2 + \eta^2 \|\nabla_{S^t} F(\mathbf{x}^{t-1})\|^2 \\ &\geq \eta^2 \|\nabla_{S^t \setminus S^{t-1}} F(\mathbf{x}^{t-1})\|^2. \end{aligned}$$

We thus have

$$F(\mathbf{x}^t) - F(\mathbf{x}^{t-1}) \leq -\frac{(1-\eta M)\eta}{2} \|\nabla_{S^t \setminus S^{t-1}} F(\mathbf{x}^{t-1})\|^2 + \epsilon.$$

Denote $\xi = \|\nabla_{S^{t-1}} F(\mathbf{x}^{t-1})\|$. We claim that

$$\|\nabla_{S^t \setminus S^{t-1}} F(\mathbf{x}^{t-1})\|^2 \geq m (F(\mathbf{x}^{t-1}) - F(\bar{\mathbf{x}})) - 2\xi^2, \quad (9)$$

which, combined with Lemma 3, immediately shows

$$F(\mathbf{x}^t) - F(\mathbf{x}^{t-1}) \leq -\frac{(1-\eta M)\eta m}{2} (F(\mathbf{x}^{t-1}) - F(\bar{\mathbf{x}})) + 2\epsilon.$$

Using Lemma 15 completes the proof.

To show (9), we consider two exhaustive cases: $|S^t \setminus S^{t-1}| \geq s$ and $|S^t \setminus S^{t-1}| < s$, and prove that (9) holds for both cases.

Case I. $|S^t \setminus S^{t-1}| \geq s$. Due to the RSC property, we have

$$\begin{aligned} &\frac{m}{2} \|\bar{\mathbf{x}} - \mathbf{x}^{t-1}\|^2 \\ &\leq F(\bar{\mathbf{x}}) - F(\mathbf{x}^{t-1}) - \langle \nabla F(\mathbf{x}^{t-1}), \bar{\mathbf{x}} - \mathbf{x}^{t-1} \rangle \\ &\leq F(\bar{\mathbf{x}}) - F(\mathbf{x}^{t-1}) + \frac{m}{2} \|\bar{\mathbf{x}} - \mathbf{x}^{t-1}\|^2 + \frac{1}{2m} \|\nabla_{S \cup S^{t-1}} F(\mathbf{x}^{t-1})\|^2 \\ &= F(\bar{\mathbf{x}}) - F(\mathbf{x}^{t-1}) + \frac{m}{2} \|\bar{\mathbf{x}} - \mathbf{x}^{t-1}\|^2 + \frac{1}{2m} \|\nabla_{S \setminus S^{t-1}} F(\mathbf{x}^{t-1})\|^2 + \frac{1}{2m} \|\nabla_{S^{t-1}} F(\mathbf{x}^{t-1})\|^2 \\ &= F(\bar{\mathbf{x}}) - F(\mathbf{x}^{t-1}) + \frac{m}{2} \|\bar{\mathbf{x}} - \mathbf{x}^{t-1}\|^2 + \frac{1}{2m} \|\nabla_{S \setminus S^{t-1}} F(\mathbf{x}^{t-1})\|^2 + \frac{1}{2m} \xi^2. \end{aligned}$$

Therefore, we get

$$\|\nabla_{S \setminus S^{t-1}} F(\mathbf{x}^{t-1})\|^2 \geq 2m (F(\mathbf{x}^{t-1}) - F(\bar{\mathbf{x}})) - \xi^2.$$

Since S^t contains the k largest absolute values of \mathbf{b}^t , and $|S^t \setminus S^{t-1}| \geq s \geq |S \setminus S^{t-1}|$, we have

$$\|\mathbf{b}_{S^t \setminus S^{t-1}}^t\|^2 \geq \|\mathbf{b}_{S \setminus S^{t-1}}^t\|^2,$$

which immediately implies (9) by noting the fact that $\mathbf{b}_{S^t \setminus S^{t-1}}^t = -\eta \nabla_{S^t \setminus S^{t-1}} F(\mathbf{x}^{t-1})$ and $\mathbf{b}_{S^t \setminus S^{t-1}}^t = -\eta \nabla_{S^t \setminus S^{t-1}} F(\mathbf{x}^{t-1})$.

Case II. $|S^t \setminus S^{t-1}| < s$. Again, we use the RSC property to obtain

$$\begin{aligned}
 & \frac{m}{2} \|\bar{\mathbf{x}} - \mathbf{x}^{t-1}\|^2 \\
 & \leq F(\bar{\mathbf{x}}) - F(\mathbf{x}^{t-1}) - \langle \nabla F(\mathbf{x}^{t-1}), \bar{\mathbf{x}} - \mathbf{x}^{t-1} \rangle \\
 & \leq F(\bar{\mathbf{x}}) - F(\mathbf{x}^{t-1}) + \frac{m}{4} \|\bar{\mathbf{x}} - \mathbf{x}^{t-1}\|^2 + \frac{1}{m} \|\nabla_{S \cup S^{t-1}} F(\mathbf{x}^{t-1})\|^2 \\
 & = F(\bar{\mathbf{x}}) - F(\mathbf{x}^{t-1}) + \frac{m}{4} \|\bar{\mathbf{x}} - \mathbf{x}^{t-1}\|^2 + \frac{1}{m} \|\nabla_{S \setminus S^{t-1}} F(\mathbf{x}^{t-1})\|^2 + \frac{1}{m} \xi^2 \\
 & = F(\bar{\mathbf{x}}) - F(\mathbf{x}^{t-1}) + \frac{m}{4} \|\bar{\mathbf{x}} - \mathbf{x}^{t-1}\|^2 + \frac{1}{m} \|\nabla_{S \setminus (S^t \cup S^{t-1})} F(\mathbf{x}^{t-1})\|^2 \\
 & \quad + \frac{1}{m} \|\nabla_{(S^t \setminus S^{t-1}) \cap S} F(\mathbf{x}^{t-1})\|^2 + \frac{1}{m} \xi^2 \\
 & \leq F(\bar{\mathbf{x}}) - F(\mathbf{x}^{t-1}) + \frac{m}{4} \|\bar{\mathbf{x}} - \mathbf{x}^{t-1}\|^2 + \frac{1}{m} \|\nabla_{S \setminus (S^t \cup S^{t-1})} F(\mathbf{x}^{t-1})\|^2 \\
 & \quad + \frac{1}{m} \|\nabla_{S^t \setminus S^{t-1}} F(\mathbf{x}^{t-1})\|^2 + \frac{1}{m} \xi^2.
 \end{aligned} \tag{10}$$

We consider the term $\|\nabla_{S \setminus (S^t \cup S^{t-1})} F(\mathbf{x}^{t-1})\|^2$ above. Actually, we have

$$\mathbf{b}_{S \setminus (S^t \cup S^{t-1})}^t = -\eta \nabla_{S \setminus (S^t \cup S^{t-1})} F(\mathbf{x}^{t-1}).$$

Since S^t contains the k largest absolute values of \mathbf{b}^t , we know that any component in \mathbf{b}_{Ω}^t is not larger than that in $\mathbf{b}_{S^t}^t$ subject to $\Omega \cap S^t = \emptyset$. In particular,

$$\frac{\|\mathbf{b}_{S \setminus (S^t \cup S^{t-1})}^t\|^2}{|S \setminus (S^t \cup S^{t-1})|} \leq \frac{\|\mathbf{b}_{(S^t \cap S^{t-1}) \setminus S}^t\|^2}{|(S^t \cap S^{t-1}) \setminus S|}.$$

Note that $|S^t \setminus S^{t-1}| < s$ implies $|(S^t \cap S^{t-1}) \setminus S| \geq k - 2s$. Therefore,

$$\begin{aligned}
 & \eta^2 \|\nabla_{S \setminus (S^t \cup S^{t-1})} F(\mathbf{x}^{t-1})\|^2 \\
 & \leq \frac{s}{k - 2s} \left\| \mathbf{x}_{(S^t \cap S^{t-1}) \setminus S}^{t-1} - \eta \nabla_{(S^t \cap S^{t-1}) \setminus S} F(\mathbf{x}^{t-1}) \right\|^2 \\
 & \leq \frac{2s}{k - 2s} \left\| \mathbf{x}_{(S^t \cap S^{t-1}) \setminus S}^{t-1} \right\|^2 + \frac{2s\eta^2}{k - 2s} \xi^2 \\
 & = \frac{2s}{k - 2s} \left\| (\mathbf{x}^{t-1} - \bar{\mathbf{x}})_{(S^t \cap S^{t-1}) \setminus S} \right\|^2 + \frac{2s\eta^2}{k - 2s} \xi^2 \\
 & \leq \frac{2s}{k - 2s} \|\mathbf{x}^{t-1} - \bar{\mathbf{x}}\|^2 + \frac{2s\eta^2}{k - 2s} \xi^2.
 \end{aligned}$$

Plugging the above into (10), we obtain

$$\begin{aligned}
 \frac{m}{2} \|\bar{\mathbf{x}} - \mathbf{x}^{t-1}\|^2 & \leq F(\bar{\mathbf{x}}) - F(\mathbf{x}^{t-1}) + \frac{m}{4} \|\bar{\mathbf{x}} - \mathbf{x}^{t-1}\|^2 + \frac{2s}{(k - 2s)\eta^2 m} \|\bar{\mathbf{x}} - \mathbf{x}^{t-1}\|^2 \\
 & \quad + \frac{1}{m} \|\nabla_{S^t \setminus S^{t-1}} F(\mathbf{x}^{t-1})\|^2 + \frac{1}{m} \left(\frac{2s}{k - 2s} + 1 \right) \xi^2.
 \end{aligned}$$

Picking $k \geq 2s + \frac{8s}{\eta^2 m^2}$ gives

$$\begin{aligned}
 \frac{m}{2} \|\bar{\mathbf{x}} - \mathbf{x}^{t-1}\|^2 & \leq F(\bar{\mathbf{x}}) - F(\mathbf{x}^{t-1}) + \frac{m}{2} \|\bar{\mathbf{x}} - \mathbf{x}^{t-1}\|^2 \\
 & \quad + \frac{1}{m} \|\nabla_{S^t \setminus S^{t-1}} F(\mathbf{x}^{t-1})\|^2 + \left(\frac{\eta^2 m}{4} + \frac{1}{m} \right) \xi^2.
 \end{aligned}$$

Since $\eta < 1/M$, $\frac{\eta^2 m}{4} + 1 < 2$. Therefore, by re-arranging the above inequality, we prove the claim (9). \square

C. Proofs for Section 3

The following result holds for all $F(\mathbf{x})$.

Lemma 18. *Assume (A1) and (A2). For any k -sparse vector \mathbf{x} and s -sparse vector $\bar{\mathbf{x}}$, we have*

$$\|\mathbf{x} - \bar{\mathbf{x}}\| \leq \kappa \|\bar{\mathbf{x}}_T\| + \frac{1}{m} \|\nabla_T F(\mathbf{x}) - \nabla_T F(\bar{\mathbf{x}})\|,$$

where T is the support set of \mathbf{x} .

Proof.

$$\begin{aligned} \|(\mathbf{x} - \bar{\mathbf{x}})_T\|^2 &= \langle \mathbf{x} - \bar{\mathbf{x}} - \tau \nabla F(\mathbf{x}) + \tau \nabla F(\bar{\mathbf{x}}), (\mathbf{x} - \bar{\mathbf{x}})_T \rangle + \tau \langle \nabla F(\mathbf{x}) - \nabla F(\bar{\mathbf{x}}), (\mathbf{x} - \bar{\mathbf{x}})_T \rangle \\ &\leq \|(\mathbf{x} - \bar{\mathbf{x}} - \tau \nabla F(\mathbf{x}) + \tau \nabla F(\bar{\mathbf{x}}))_T\| \cdot \|(\mathbf{x} - \bar{\mathbf{x}})_T\| + \tau \|\nabla_T F(\mathbf{x}) - \nabla_T F(\bar{\mathbf{x}})\| \cdot \|(\mathbf{x} - \bar{\mathbf{x}})_T\| \\ &\leq \|\mathbf{x} - \bar{\mathbf{x}} - \tau \nabla_{T \cup S} F(\mathbf{x}) + \tau \nabla_{T \cup S} F(\bar{\mathbf{x}})\| \cdot \|(\mathbf{x} - \bar{\mathbf{x}})_T\| + \tau \|\nabla_T F(\mathbf{x}) - \nabla_T F(\bar{\mathbf{x}})\| \cdot \|(\mathbf{x} - \bar{\mathbf{x}})_T\| \\ &\leq \rho \|\mathbf{x} - \bar{\mathbf{x}}\| \cdot \|(\mathbf{x} - \bar{\mathbf{x}})_T\| + \tau \|\nabla_T F(\mathbf{x}) - \nabla_T F(\bar{\mathbf{x}})\| \cdot \|(\mathbf{x} - \bar{\mathbf{x}})_T\|. \end{aligned}$$

Dividing both sides by $\|(\mathbf{x} - \bar{\mathbf{x}})_T\|$ gives

$$\|(\mathbf{x} - \bar{\mathbf{x}})_T\| \leq \rho \|\mathbf{x} - \bar{\mathbf{x}}\| + \tau \|\nabla_T F(\mathbf{x}) - \nabla_T F(\bar{\mathbf{x}})\|.$$

On the other hand,

$$\begin{aligned} \|\mathbf{x} - \bar{\mathbf{x}}\| &\leq \|(\mathbf{x} - \bar{\mathbf{x}})_T\| + \|(\mathbf{x} - \bar{\mathbf{x}})_{\bar{T}}\| \\ &\leq \rho \|\mathbf{x} - \bar{\mathbf{x}}\| + \tau \|\nabla_T F(\mathbf{x}) - \nabla_T F(\bar{\mathbf{x}})\| + \|\bar{\mathbf{x}}_{\bar{T}}\|. \end{aligned}$$

Hence, we have

$$\|\mathbf{x} - \bar{\mathbf{x}}\| \leq \frac{1}{1-\rho} \|\bar{\mathbf{x}}_{\bar{T}}\| + \frac{\tau}{1-\rho} \|\nabla_T F(\mathbf{x}) - \nabla_T F(\bar{\mathbf{x}})\|.$$

Picking $\tau = 1/M$ completes the proof. \square

In view of the exact (HTP3), we have

$$\|\mathbf{x}^t - \bar{\mathbf{x}}\| \leq \kappa \|\bar{\mathbf{x}}_{S^t}\| + \frac{1}{m} \|\nabla_k F(\bar{\mathbf{x}})\|. \quad (11)$$

Now we present the crucial lemma. It is inspired by Bouchot et al. (2016) but we show a more general result.

Lemma 19. *Consider the HTP algorithm. Assume (A1) and (A2). Further assume that the sequence of $\{\mathbf{x}^t\}_{t \geq 0}$ satisfies*

$$\begin{aligned} \|\mathbf{x}^t - \bar{\mathbf{x}}\| &\leq \alpha \cdot \beta^t \|\mathbf{x}^0 - \bar{\mathbf{x}}\| + \phi, \\ \|\mathbf{x}^t - \bar{\mathbf{x}}\| &\leq \gamma \|\bar{\mathbf{x}}_{S^t}\| + \psi, \end{aligned}$$

for positive $\alpha, \phi, \gamma, \psi$ and $0 < \beta < 1$. Suppose that at the n -th iteration ($n \geq 0$), S^n contains the indices of top p (in magnitude) elements of $\bar{\mathbf{x}}$. Then, for any integer $1 \leq q \leq s - p$, there exists an integer $r \geq 1$ determined by

$$\sqrt{2} \|\bar{\mathbf{x}}_{p+q}\| > \alpha \gamma \cdot \beta^{r-1} \|\bar{\mathbf{x}}_{\{p+1, \dots, s\}}\| + \theta$$

where

$$\theta = \alpha \psi + \phi + \frac{1}{m} \|\nabla_2 F(\bar{\mathbf{x}})\|,$$

such that S^{n+r} contains the indices of top $p + q$ elements of $\bar{\mathbf{x}}$ provided that $\theta \leq \sqrt{2} \lambda \bar{\mathbf{x}}_{\min}$ for some $\lambda \in (0, 1)$.

Proof. Without loss of generality, we presume that the elements in $\bar{\mathbf{x}}$ are in descending order by their magnitude, i.e., $|\bar{\mathbf{x}}_1| \geq |\bar{\mathbf{x}}_2| \geq \dots \geq |\bar{\mathbf{x}}_s|$. We aim at deriving a condition under which $[p+q] \subset \mathcal{S}^{n+r}$. To this end, it suffices to enforce

$$\min_{j \in [p+q]} |\mathbf{b}_j^{n+r}| > \max_{i \in \bar{\mathcal{S}}} |\mathbf{b}_i^{n+r}|. \quad (12)$$

On one hand, for any $j \in [p+q]$,

$$\begin{aligned} |\mathbf{b}_j^{n+r}| &= \left| (\mathbf{x}^{n+r-1} - \eta \nabla F(\mathbf{x}^{n+r-1}))_j \right| \\ &\geq |\bar{\mathbf{x}}_j| - \left| (\mathbf{x}^{n+r-1} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}^{n+r-1}))_j \right| \\ &\geq |\bar{\mathbf{x}}_{p+q}| - \left| (\mathbf{x}^{n+r-1} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}^{n+r-1}))_j \right|. \end{aligned}$$

On the other hand, for all $i \in \bar{\mathcal{S}}$,

$$|\mathbf{b}_i^{n+r}| = \left| (\mathbf{x}^{n+r-1} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}^{n+r-1}))_i \right|.$$

Hence, we know that to guarantee (12), it suffices to ensure for all $j \in [p+q]$ and $i \in \bar{\mathcal{S}}$ that

$$|\bar{\mathbf{x}}_{p+q}| > \left| (\mathbf{x}^{n+r-1} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}^{n+r-1}))_j \right| + \left| (\mathbf{x}^{n+r-1} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}^{n+r-1}))_i \right|.$$

Note that the right-hand side is upper bounded as follows:

$$\begin{aligned} &\frac{1}{\sqrt{2}} \left| (\mathbf{x}^{n+r-1} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}^{n+r-1}))_j \right| + \frac{1}{\sqrt{2}} \left| (\mathbf{x}^{n+r-1} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}^{n+r-1}))_i \right| \\ &\leq \left\| (\mathbf{x}^{n+r-1} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}^{n+r-1}))_{\{j,i\}} \right\| \\ &\leq \left\| (\mathbf{x}^{n+r-1} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}^{n+r-1}) + \eta \nabla F(\bar{\mathbf{x}}))_{\{j,i\}} \right\| + \eta \|\nabla_{\{j,i\}} F(\bar{\mathbf{x}})\| \\ &\leq \rho \|\mathbf{x}^{n+r-1} - \bar{\mathbf{x}}\| + \eta \|\nabla_2 F(\bar{\mathbf{x}})\| \\ &\leq \rho \alpha \cdot \beta^{r-1} \|\mathbf{x}^n - \bar{\mathbf{x}}\| + \rho \phi + \eta \|\nabla_2 F(\bar{\mathbf{x}})\|. \end{aligned}$$

Moreover,

$$\|\mathbf{x}^n - \bar{\mathbf{x}}\| \leq \gamma \|\bar{\mathbf{x}}_{\bar{\mathcal{S}}^n}\| + \psi \leq \gamma \|\bar{\mathbf{x}}_{[p]}\| + \psi = \gamma \|\bar{\mathbf{x}}_{\{p+1, \dots, s\}}\| + \psi.$$

Put all together, we have

$$\begin{aligned} &\frac{1}{\sqrt{2}} \left| (\mathbf{x}^{n+r-1} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}^{n+r-1}))_j \right| + \frac{1}{\sqrt{2}} \left| (\mathbf{x}^{n+r-1} - \bar{\mathbf{x}} - \eta \nabla F(\mathbf{x}^{n+r-1}))_i \right| \\ &\leq \rho \alpha \gamma \cdot \beta^{r-1} \|\bar{\mathbf{x}}_{\{p+1, \dots, s\}}\| + \rho \alpha \psi + \rho \phi + \eta \|\nabla_2 F(\bar{\mathbf{x}})\| \\ &\leq \alpha \gamma \cdot \beta^{r-1} \|\bar{\mathbf{x}}_{\{p+1, \dots, s\}}\| + \alpha \psi + \phi + \frac{1}{m} \|\nabla_2 F(\bar{\mathbf{x}})\|. \end{aligned}$$

Therefore, when

$$\sqrt{2} |\bar{\mathbf{x}}_{p+q}| > \alpha \gamma \cdot \beta^{r-1} \|\bar{\mathbf{x}}_{\{p+1, \dots, s\}}\| + \alpha \psi + \phi + \frac{1}{m} \|\nabla_2 F(\bar{\mathbf{x}})\|,$$

we always have (12). Note that the above holds as far as $\alpha \psi + \phi + \frac{1}{m} \|\nabla_2 F(\bar{\mathbf{x}})\|$ is strictly smaller than $\sqrt{2} |\bar{\mathbf{x}}_s|$. \square

With Lemma 19, we show the following general theorem.

Theorem 20. *Assume same conditions as in Lemma 19. Then HTP successfully identifies the support of $\bar{\mathbf{x}}$ using $\left(\frac{\log 2}{2 \log(1/\beta)} + \frac{\log(\alpha \gamma / (1-\lambda))}{\log(1/\beta)} + 2 \right) s$ number of iterations.*

Proof. Without loss of generality, we presume that the elements in $\bar{\mathbf{x}}$ are in descending order by their magnitude, i.e., $|\bar{\mathbf{x}}_1| \geq |\bar{\mathbf{x}}_2| \geq \dots \geq |\bar{\mathbf{x}}_s|$. We partition the support set $[s]$ into K folds S_1, S_2, \dots, S_K , where each S_i is defined as follows:

$$S_i = \{s_{i-1} + 1, \dots, s_i\}, \forall 1 \leq i \leq K.$$

Here, $s_0 = 0$ and for all $1 \leq i \leq K$, the quantity s_i is inductively given by

$$s_i = \max \left\{ q : s_{i-1} + 1 \leq q \leq s \text{ and } |\bar{\mathbf{x}}_q| > \frac{1}{\sqrt{2}} |\bar{\mathbf{x}}_{s_{i-1}+1}| \right\}.$$

In this way, we note that for any two index sets S_i and S_j , $S_i \cap S_j = \emptyset$ if $i \neq j$. We also know by the definition of s_i that

$$|\bar{\mathbf{x}}_{s_i+1}| \leq \frac{1}{\sqrt{2}} |\bar{\mathbf{x}}_{s_{i-1}+1}|, \forall 1 \leq i \leq K - 1. \quad (13)$$

Now we show that after a finite number of iterations, say n , the union of the S_i 's is contained in S^n . To this end, we prove that for all $0 \leq i \leq K$,

$$\bigcup_{t=0}^i S_t \subset S^{n_0+n_1+\dots+n_i} \quad (14)$$

for some n_i 's given below.

We pick $n_0 = 0$ and it is easy to verify that $S_0 \subset S^0$. Now suppose that (14) holds for $i - 1$. That is, the index set of the top s_{i-1} elements of $\bar{\mathbf{x}}$ is contained in $S^{n_0+\dots+n_{i-1}}$. Due to Lemma 19, (14) holds for i as long as n_i satisfies

$$\sqrt{2} |\bar{\mathbf{x}}_{s_i}| > \alpha\gamma \cdot \beta^{n_i-1} \|\bar{\mathbf{x}}_{\{s_{i-1}+1, \dots, s\}}\| + \theta. \quad (15)$$

Note that

$$\begin{aligned} \|\bar{\mathbf{x}}_{\{s_{i-1}+1, \dots, s\}}\|^2 &= \|\bar{\mathbf{x}}_{S_i}\|^2 + \dots + \|\bar{\mathbf{x}}_{S_K}\|^2 \\ &\leq (\bar{\mathbf{x}}_{s_{i-1}+1})^2 |S_i| + \dots + (\bar{\mathbf{x}}_{s_{r-1}+1})^2 |S_K| \\ &\leq (\bar{\mathbf{x}}_{s_{i-1}+1})^2 (|S_i| + 2^{-1} |S_{i+1}| + \dots + 2^{i-K} |S_K|) \\ &< 2(\bar{\mathbf{x}}_{s_i})^2 (|S_i| + 2^{-1} |S_{i+1}| + \dots + 2^{i-K} |S_K|), \end{aligned}$$

where the second inequality follows from (13) and the last inequality follows from the definition of q_i . Denote for simplicity

$$T_i := |S_i| + 2^{-1} |S_{i+1}| + \dots + 2^{i-K} |S_K|.$$

As we assume $\theta \leq \sqrt{2}\lambda\bar{\mathbf{x}}_{\min}$, we get

$$\alpha\gamma \cdot \beta^{n_i-1} \|\bar{\mathbf{x}}_{\{s_{i-1}+1, \dots, s\}}\| + \theta < \sqrt{2}\alpha\gamma |\bar{\mathbf{x}}_{s_i}| \beta^{n_i-1} \sqrt{T_i} + \sqrt{2}\lambda |\bar{\mathbf{x}}_{s_i}|.$$

Picking

$$n_i = \log_{1/\beta} \frac{\alpha\gamma\sqrt{T_i}}{1-\lambda} + 2$$

guarantees (15). It remains to calculate the total number of iterations. In fact, we have

$$\begin{aligned}
 n &= n_0 + n_1 + \dots + n_K \\
 &= \frac{1}{2 \log(1/\beta)} \sum_{i=1}^K \log T_i + K \cdot \frac{\log(\alpha\gamma/(1-\lambda))}{\log(1/\beta)} + 2K \\
 &\stackrel{\zeta_1}{\leq} \frac{K}{2 \log(1/\beta)} \log \left(\frac{1}{K} \sum_{i=1}^K T_i \right) + \left(\frac{\log(\alpha\gamma/(1-\lambda))}{\log(1/\beta)} + 2 \right) K \\
 &\stackrel{\zeta_2}{\leq} \frac{K}{2 \log(1/\beta)} \log \left(\frac{2}{K} \sum_{i=1}^K |S_i| \right) + \left(\frac{\log(\alpha\gamma/(1-\lambda))}{\log(1/\beta)} + 2 \right) K \\
 &= \frac{K}{2 \log(1/\beta)} \log \frac{2s}{K} + \left(\frac{\log(\alpha\gamma/(1-\lambda))}{\log(1/\beta)} + 2 \right) K \\
 &\stackrel{\zeta_3}{\leq} \left(\frac{\log 2}{2 \log(1/\beta)} + \frac{\log(\alpha\gamma/(1-\lambda))}{\log(1/\beta)} + 2 \right) s.
 \end{aligned}$$

Above, ζ_1 immediately follows by observing that the logarithmic function is concave. ζ_2 uses the fact that after rearrangement, the coefficient of $|S_i|$ is $\sum_{j=0}^{i-1} 2^{-j}$ which is always smaller than 2. Finally, since the function $r \log(2s/r)$ is monotonically increasing with respect to r and $1 \leq r \leq s$, ζ_3 follows. \square

Combining this theorem, Lemma 19 and specific results in Prop. 2, Prop. 4 and Prop. 5 gives the main theorems in Section 3.