

ISyE8813  
Convergence of the HPE

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## 1 Convergence of the HPE framework

Recall the HPE framework

**Inexact IPP**

- 0) Let  $z_0 \in \mathbb{R}^n$  and  $\sigma \in [0, 1]$  be given and set  $k = 1$ .
- 1) Choose  $\lambda_k > 0$  and find  $(x_k, \tilde{x}_k, \varepsilon_k) \in \mathbb{R}^n \times \mathbb{R}^n \times \mathbb{R}_+$  such that

$$\tilde{v}_k := \frac{z_{k-1} - z_k}{\lambda_k} \in T^{\varepsilon_k}(\tilde{z}_k)$$
$$\|\tilde{z}_k - z_k\|^2 + 2\lambda_k \varepsilon_k \leq \sigma^2 \|\tilde{z}_k - z_{k-1}\|^2$$

- 2) Set  $k \leftarrow k + 1$  and go to step 1.

## Pointwise Convergence

**Lemma 1:** For every  $k \geq 1$  and  $z \in \mathbb{R}^n$ , have

$$\begin{aligned} & \|z - z_{k-1}\|^2 - \|z - z_k\|^2 \\ &= 2\lambda_k \langle \tilde{z}_k - z, \tilde{v}_k \rangle + \|\tilde{z}_k - z_{k-1}\|^2 - \|\tilde{z}_k - z_k\|^2 \end{aligned}$$

**Proof:** Have

$$\begin{aligned} & \|z - z_{k-1}\|^2 - \|z - z_k\|^2 \\ &= 2\langle z - z_k, z_k - z_{k-1} \rangle + \|z_k - z_{k-1}\|^2 \\ &= 2\langle z - \tilde{z}_k, z_k - z_{k-1} \rangle + 2\langle \tilde{z}_k - z_k, z_k - z_{k-1} \rangle + \|z_k - z_{k-1}\|^2 \\ &= 2\langle z - \tilde{z}_k, z_k - z_{k-1} \rangle + \|\tilde{z}_k - z_{k-1}\|^2 - \|\tilde{z}_k - z_k\|^2 \\ &= -2\lambda_k \langle z - \tilde{z}_k, \tilde{v}_k \rangle + \|\tilde{z}_k - z_{k-1}\|^2 - \|\tilde{z}_k - z_k\|^2 \end{aligned}$$

**Lemma 2:** For every  $k \geq 1$  and  $z_* \in T^{-1}(0)$ , have

$$\|z_* - z_{k-1}\|^2 - \|z_* - z_k\|^2 \geq (1 - \sigma^2) \|\tilde{z}_k - z_{k-1}\|^2 \geq 0$$

**Proof:** If  $z_* \in T^{-1}(0)$  then it follows that  $(z_*, 0) \in \text{gr } T$ . Moreover, since  $\tilde{v}_k \in T^{\varepsilon_k}(\tilde{z}_k)$ , we have  $(\tilde{z}_k, \tilde{v}_k) \in \text{gr } T^{\varepsilon_k}$ . Hence, it follows from the definition of  $T^{\varepsilon_k}$  that

$$\langle \tilde{z}_k - z_*, \tilde{v}_k \rangle = \langle \tilde{z}_k - z_*, \tilde{v}_k - 0 \rangle \geq -\varepsilon_k$$

This inequality and Lemma 1 with  $z = z_*$  then imply that

$$\begin{aligned} & \|z_* - z_{k-1}\|^2 - \|z_* - z_k\|^2 \\ &= 2\lambda_k \langle \tilde{z}_k - z_*, \tilde{v}_k \rangle + \|\tilde{z}_k - z_{k-1}\|^2 - \|\tilde{z}_k - z_k\|^2 \\ &\geq -2\lambda_k \varepsilon_k + \|\tilde{z}_k - z_{k-1}\|^2 - \|\tilde{z}_k - z_k\|^2 \\ &= \|\tilde{z}_k - z_{k-1}\|^2 - \left[ \|\tilde{z}_k - z_k\|^2 + 2\lambda_k \varepsilon_k \right] \\ &\geq \|\tilde{z}_k - z_{k-1}\|^2 - \sigma^2 \|\tilde{z}_k - z_{k-1}\|^2 \end{aligned}$$

where the last inequality is due to the HPE inequality condition

**Lemma 3:** For every  $K \geq 1$  and  $z_* \in T^{-1}(0)$ , have

$$\|z_* - z_0\|^2 - \|z_* - z_K\|^2 \geq (1 - \sigma^2) \sum_{k=1}^K \|\tilde{z}_k - z_{k-1}\|^2$$

**Proof:** Follows by adding the inequality in Lemma 2 from  $k = 1$  to  $k = K$ .

**Lemma 4:** For every  $K \geq 1$ , have

$$\max \left\{ \frac{2\lambda_k \varepsilon_k}{\sigma^2}, \frac{\lambda_k^2 \|\tilde{v}_k\|^2}{(1 + \sigma)^2} \right\} \leq \|\tilde{z}_k - z_{k-1}\|^2$$

**Proof:** The first inequality of the Lemma follows from the HPE inequality condition. The second one is due to the fact that

$$\begin{aligned} \lambda_k \|\tilde{v}_k\| &= \|z_k - z_{k-1}\| \\ &= \|z_k - \tilde{z}_k + \tilde{z}_k - z_{k-1}\| \\ &\leq \|z_k - \tilde{z}_k\| + \|\tilde{z}_k - z_{k-1}\| \\ &\leq \sigma \|\tilde{z}_k - z_{k-1}\| + \|\tilde{z}_k - z_{k-1}\| \\ &= (1 + \sigma) \|\tilde{z}_k - z_{k-1}\| \end{aligned}$$

where the second inequality is due to the HPE inequality condition

**Lemma 5:** For every  $K \geq 1$ , there exists  $k \in \{1, \dots, K\}$  such that

$$\begin{aligned}\varepsilon_k &\leq \frac{\sigma^2 d_0^2}{2\lambda_k(1-\sigma^2)K}, \\ \|\tilde{v}_k\|^2 &\leq \frac{(1+\sigma)^2 d_0^2}{\lambda_k^2(1-\sigma^2)K}\end{aligned}$$

where  $d_0 = \min\{\|z_* - z_0\| : z_* \in T^{-1}(0)\}$ .

As a consequence, if there exists  $\underline{\lambda} > 0$  such that  $\lambda_k \geq \underline{\lambda}$  for every  $k \in \{1, \dots, K\}$ , then there exists  $k \in \{1, \dots, K\}$  such that

$$\max\{\varepsilon_k, \|\tilde{v}_k\|^2\} = \mathcal{O}\left(\frac{1}{K}\right)$$

**Proof:** Let  $z_*$  be the closest point to  $z_0$  lying in  $T^{-1}(0)$ . Hence,  $d_0 = \|z_* - z_0\|$ . Then, it follows from Lemma 3 that

$$K \min_{k=1, \dots, K} \|\tilde{z}_k - z_{k-1}\|^2 \leq \sum_{k=1}^K \|\tilde{z}_k - z_{k-1}\|^2 \leq \frac{d_0^2}{1-\sigma^2}$$

Thus, there exists  $k \in \{1, \dots, K\}$  such that

$$\frac{d_0^2}{K(1-\sigma^2)} \geq \|\tilde{z}_k - z_{k-1}\|^2 \geq \max\left\{\frac{2\lambda_k \varepsilon_k}{\sigma^2}, \frac{\lambda_k^2 \|\tilde{v}_k\|^2}{(1+\sigma)^2}\right\}$$

where the last inequality is due to Lemma 4.

## Ergodic Convergence

**Technical Lemma:** Assume that  $T$  is maximal monotone and that  $\text{gr } T^\varepsilon \neq \emptyset$  for some  $\varepsilon \in \mathbb{R}$ . Then,  $\varepsilon \geq 0$

**Proof:** Assume for contradiction that  $(y, w) \in \text{gr } T^\varepsilon$  for some  $\varepsilon < 0$  and  $(y, w) \in \mathbb{R}^n \times \mathbb{R}^n$ . Then

$$\langle w - v, y - x \rangle \geq -\varepsilon > 0 \quad \forall (x, v) \in \text{gr } T$$

Have  $(w, y) \in \text{gr } T$  since otherwise the above inequality with  $(x, v) = (y, w)$  would give an absurd. Consider now the multi-valued operator  $\tilde{T}$  such that

$$\text{gr } \tilde{T} = T \cup \{(w, y)\}$$

It follows from the monotonicity of  $T$  and the above inequality that  $\tilde{T}$  is monotone. Moreover,  $\tilde{T}$  is larger than  $T$  and includes  $T$ . These two conclusions then contradict the assumption that  $T$  is a maximal monotone operator

**Lemma 6:** For every  $K \geq 1$ , we have

$$\tilde{v}_K^a \in T^{\varepsilon_K^a}(\tilde{z}_K^a) \quad (1)$$

where

$$\begin{aligned} \tilde{v}_K^a &:= \frac{1}{\Lambda_K} \sum_{k=1}^K \lambda_k \tilde{v}_k = \frac{z_0 - z_K}{\Lambda_K} & \tilde{z}_K^a &:= \frac{1}{\Lambda_K} \sum_{k=1}^K \lambda_k \tilde{z}_k \\ \varepsilon_K^a &:= \frac{1}{\Lambda_K} \sum_{k=1}^K \lambda_k [\langle \tilde{v}_k, \tilde{z}_k - \tilde{z}_K^a \rangle + \varepsilon_k] \geq 0 \end{aligned}$$

and

$$\Lambda_K := \sum_{k=1}^K \lambda_k$$

**Proof:** Let  $(z, v) \in \text{gr } T$  be given. The HPE inclusion  $\tilde{v}_k \in T^{\varepsilon_k}(\tilde{z}_k)$  implies that

$$\langle \tilde{v}_k - v, \tilde{z}_k - z \rangle \geq -\varepsilon_k$$

or equivalently,

$$\langle \tilde{v}_k, \tilde{z}_k - z \rangle + \varepsilon_k \geq \langle v, \tilde{z}_k - z \rangle$$

Hence

$$\frac{1}{\Lambda_K} \sum_{k=1}^K \lambda_k [\langle \tilde{v}_k, \tilde{z}_k - z \rangle + \varepsilon_k] \geq \frac{1}{\Lambda_K} \sum_{k=1}^K \lambda_k \langle v, \tilde{z}_k - z \rangle = \langle v, \tilde{z}_K^a - z \rangle$$

where the equality is due to the definition of  $\tilde{z}_K^a$ . Now let

$$\Gamma_K(z) := \frac{1}{\Lambda_K} \sum_{k=1}^K \lambda_k [\langle \tilde{z}_k - z, \tilde{v}_k \rangle + \varepsilon_K]$$

Then

$$\Gamma_K(z) \geq \langle v, \tilde{z}_K^a - z \rangle$$

Note that  $\Gamma_K(\cdot)$  is an affine function such that

$$\nabla \Gamma_K = -\tilde{v}_K^a, \quad \Gamma_K(\tilde{z}_K^a) = \varepsilon_K^a$$

where these two identities follows from the definitions of  $\tilde{v}_K^a$  and  $\varepsilon_K^a$ . Thus,

$$\begin{aligned} \Gamma_K(z) &= \Gamma_K(\tilde{z}_K^a) + \langle -\nabla \Gamma_K, \tilde{z}_K^a - z \rangle \\ &= \varepsilon_K^a + \langle \tilde{v}_K^a, \tilde{z}_K^a - z \rangle \end{aligned}$$

We then conclude that

$$\varepsilon_K^a + \langle \tilde{v}_K^a, \tilde{z}_K^a - z \rangle \geq \langle v, \tilde{z}_K^a - z \rangle$$

Since this holds for every  $(z, v) \in \text{gr } T$ , we conclude that (1) holds. The fact that  $\varepsilon_K^a \geq 0$  follows from (1) and the Technical Lemma above.

**Lemma 7:** For every  $K \geq 1$ , we have

$$\|\tilde{v}_K^a\| \leq \frac{2d_0}{\Lambda_K}$$

**Proof:** Have

$$\tilde{v}_K^a = \frac{1}{\Lambda_K} \sum_{k=1}^K \lambda_k \tilde{v}_k = \frac{1}{\Lambda_K} \sum_{k=1}^K (z_{k-1} - z_k) = \frac{z_0 - z_K}{\Lambda_K}$$

Hence,

$$\begin{aligned} \|\tilde{v}_K^a\| &= \frac{\|z_0 - z_K\|}{\Lambda_K} \leq \frac{\|z_0 - z_* + z_* - z_K\|}{\Lambda_K} \\ &\leq \frac{\|z_0 - z_*\| + \|z_K - z_*\|}{\Lambda_K} \\ &\leq \frac{2\|z_0 - z_*\|}{\Lambda_K} = \frac{2d_0}{\Lambda_K} \end{aligned}$$

**Lemma 8:** For every  $k \geq 1$  and  $z \in \mathbb{R}^n$ , have

$$\|z - z_{k-1}\|^2 - \|z - z_k\|^2 \geq 2\lambda_k \gamma_k(z) + (1 - \sigma^2) \|\tilde{z}_k - z_{k-1}\|^2$$

where

$$\gamma_k(z) := \langle \tilde{z}_k - z, \tilde{v}_k \rangle + \varepsilon_k$$

**Proof:** By Lemma 1 and the definition of  $\gamma_k(\cdot)$ , have

$$\begin{aligned} & \|z - z_{k-1}\|^2 - \|z - z_k\|^2 \\ &= 2\lambda_k \langle \tilde{z}_k - z, \tilde{v}_k \rangle + \|\tilde{z}_k - z_{k-1}\|^2 - \|\tilde{z}_k - z_k\|^2 \\ &= 2\lambda_k \gamma_k(z) + \|\tilde{z}_k - z_{k-1}\|^2 - \|\tilde{z}_k - z_k\|^2 - 2\lambda_k \varepsilon_k \\ &\geq 2\lambda_k \gamma_k(z) + (1 - \sigma^2) \|\tilde{z}_k - z_{k-1}\|^2 \end{aligned}$$

where the inequality is due to the HPE inequality condition.

**Lemma 9:** For every  $K \geq 1$  and  $z \in \mathbb{R}^n$ , have

$$\|z - z_0\|^2 - \|z - z_K\|^2 \geq 2\Lambda_K \Gamma_K(z) + (1 - \sigma^2) \sum_{k=1}^K \|\tilde{z}_k - z_{k-1}\|^2$$

where

$$\Gamma_K(z) := \frac{1}{\Lambda_K} \sum_{k=1}^K \lambda_k \gamma_k(z) = \frac{1}{\Lambda_K} \sum_{k=1}^K \lambda_k [\langle \tilde{z}_k - z, \tilde{v}_k \rangle + \varepsilon_k]$$

**Proof:** This result follows from the definition of  $\Gamma_k(\cdot)$  and by adding the inequality of Lemma 8 from  $k = 1$  to  $k = K$

**Lemma 10:** For every  $K \geq 1$  and  $z \in \mathbb{R}^n$ , have

$$\|\tilde{z}_K^a - z_0\|^2 - \|\tilde{z}_K^a - z_K\|^2 \geq 2\Lambda_K \varepsilon_K^a + (1 - \sigma^2) \sum_{k=1}^K \|\tilde{z}_k - z_{k-1}\|^2$$

**Proof:** This result follows from the fact that

$$\varepsilon_K^a = \Gamma_K(\tilde{z}_K^a)$$

and the previous lemma with  $z = \tilde{z}_K^a$

**Lemma 11:** For every  $K \geq 1$  and  $z \in \mathbb{R}^n$ , have

$$\varepsilon_K^a \leq \left(4 + \frac{\sigma^2}{1 - \sigma^2}\right) \frac{d_0^2}{\Lambda_K}$$

**Proof:** The previous lemma implies that

$$\varepsilon_K^a \leq \frac{\|\tilde{z}_K^a - z_0\|^2}{2\Lambda_K}$$

Now,

$$\begin{aligned} \|\tilde{z}_K^a - z_0\|^2 &\leq \max \{ \|\tilde{z}_k - z_0\|^2 : k = 1, \dots, K \} \\ &\leq \max 2 \{ \|\tilde{z}_k - z_k\|^2 + \|z_k - z_0\|^2 : k = 1, \dots, K \} \\ &\leq 2 \max \{ \|\tilde{z}_k - z_k\|^2 + 4d_0^2 : k = 1, \dots, K \} \\ &\leq 8d_0^2 + 2\sigma^2 \max \{ \|\tilde{z}_k - z_{k-1}\|^2 : k = 1, \dots, K \} \\ &\leq 8d_0^2 + 2\sigma^2 \frac{d_0^2}{1 - \sigma^2} = 2 \left(4 + \frac{\sigma^2}{1 - \sigma^2}\right) d_0^2 \end{aligned}$$

## 2 Generalized HPE framework (overview)

Consider the MIP

$$0 \in T(z)$$

where  $T : \mathbb{R}^n \rightrightarrows \mathbb{R}^n$  is maximal monotone

Assume that for some semi-norm in  $\mathbb{R}^n$ , the following conditions hold:

- 1)  $T^{-1}(0) \neq \emptyset$
- 2) there exists  $m, M > 0$  such that for every  $z, z' \in \mathbb{R}^n$ , have

$$\begin{aligned} (dw)_z(z') &\geq \frac{m}{2} \|z' - z\|^2 \\ \|\nabla w(z') - \nabla w(z)\|^* &\leq M \|z' - z\| \end{aligned}$$

where

$$\|\cdot\|^* := \sup\{\langle \cdot, v \rangle : \|v\| \leq 1\}$$

Condition 2) implies that

$$\frac{m}{2} \|z - z'\|^2 \leq (dw)_z(z') \leq \frac{M}{2} \|z - z'\|^2 \quad \forall z, z' \in Z \quad (2)$$

**Example:** If

$$w(\cdot) = (1/2) \|\cdot\|_Q^2$$

where  $Q$  is a self-adjoint positive semidefinite linear operator, then  $w$  satisfies condition 2 with  $(m, M) = (1, 1)$ .

**Proposition 2.1** *If  $Q : \mathbb{R}^n \rightarrow \mathbb{R}^n$  is a self-adjoint positive semidefinite linear operator, then the semi-norm*

$$\|\cdot\| := \langle \cdot, Q(\cdot) \rangle^{1/2}$$

*satisfies the following statements:*

- (a)  $\text{dom } \|\cdot\|^* = \text{Im}(Q)$  and

$$\|Qz\|^* = \|z\| \quad \forall z \in \mathbb{R}^n$$

- (b) *if  $Q$  is invertible, then*

$$\|z\|^* = \langle Q^{-1}z, z \rangle^{1/2} \quad \forall z \in \mathbb{R}^n$$

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**Algorithm 1** (Inexact PPM framework with Bregman distance)

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0. Let  $z_0 \in \mathbb{R}^n$  and  $\sigma \in [0, 1]$  be given.  
1. Find  $\lambda > 0$  and  $(z, \tilde{z}, \varepsilon) \in \mathbb{R}^n \times \mathbb{R}^n \times \mathbb{R}_+$  such that

$$\frac{\nabla w(z_0) - \nabla w(z)}{\lambda} \in T^\varepsilon(\tilde{z}) \quad (3)$$

$$(dw)_z(\tilde{z}) + \lambda\varepsilon \leq \sigma(dw)_{z_0}(\tilde{z}) \quad (4)$$

2. Set  $z_0 \leftarrow z$  and go to step 1.
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Hence, sequence-wise, we have for every  $k \geq 1$  that

$$r_k := \frac{\nabla w(z_{k-1}) - \nabla w(z_k)}{\lambda_k} \in T^{\varepsilon_k}(\tilde{z}_k) \quad (5)$$

$$(dw)_z(\tilde{z}_k) + \lambda_k \varepsilon_k \leq \sigma(dw)_{z_{k-1}}(\tilde{z}_k) \quad (6)$$

**Proposition 2.2 (Pointwise)** *Assume that  $\sigma < 1$  and  $\lambda_k \geq \underline{\lambda}$  for every  $k \geq 1$ . Then, for every  $k \geq 1$ , there exists  $i \leq k$  such that*

$$\|r_i\|^* \leq \frac{2M}{\underline{\lambda}\sqrt{mk}} \sqrt{\frac{(1+\sigma)(dw)_0}{1-\sigma}} = \mathcal{O}\left(\frac{1}{\underline{\lambda}\sqrt{k}}\right)$$

and

$$\varepsilon_i \leq \frac{(1+\sigma)(dw)_0}{(1-\sigma)\underline{\lambda}k} = \mathcal{O}\left(\frac{1}{\underline{\lambda}k}\right)$$

where  $r_i$  is as in (5) and

$$(dw)_0 := \inf \{(dw)_{z_0}(z_*) : z_* \in T^{-1}(0)\}$$

For  $k \geq 1$ , define  $\Lambda_k := \sum_{i=1}^k \lambda_i$  and the ergodic iterate  $(\tilde{z}_k^a, r_k^a, \varepsilon_k^a)$  as

$$\tilde{z}_k^a = \frac{1}{\Lambda_k} \sum_{i=1}^k \lambda_i \tilde{z}_i, \quad r_k^a := \frac{1}{\Lambda_k} \sum_{i=1}^k \lambda_i r_i, \quad \varepsilon_k^a := \frac{1}{\Lambda_k} \sum_{i=1}^k \lambda_i (\varepsilon_i + \langle r_i, \tilde{z}_i - \tilde{z}_k^a \rangle). \quad (7)$$

**Theorem 2.3 (Ergodic convergence of the NE-HPE)** *For every  $k \geq 1$ , we have*

$$r_k^a \in T^{\varepsilon_k^a}(\tilde{z}_k^a)$$

and

$$\|r_k^a\|^* \leq \frac{2\sqrt{2}M(dw_0)^{1/2}}{\sqrt{m}\Lambda_k}, \quad \varepsilon_k^a \leq \left(\frac{3M}{m}\right) \left[\frac{3(dw)_0 + \sigma\theta_k}{\Lambda_k}\right].$$

where

$$\theta_k := \max_{i=1, \dots, k} (dw)_{z_{i-1}}(\tilde{z}_i). \quad (8)$$

Moreover, the sequence  $\{\theta_k\}$  is bounded under either one of the following situations:

(a)  $\sigma < 1$ , in which case

$$\theta_k \leq \frac{(dw)_0}{1 - \sigma}; \quad (9)$$

(b)  $\text{Dom } T$  is bounded, in which case

$$\theta_k \leq \frac{2M}{m} [(dw)_0 + D]$$

where

$$D := \sup \{ \min \{ (dw)_y(y'), (dw)_{y'}(y) \} : y, y' \in \text{Dom } T \}$$