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# The Implicit Bias of AdaGrad on Separable Data

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## Appendix

To simplify notation, we denote

$$S_i(t) = \sum_{\tau=0}^t g_i(\tau)^2,$$

for all  $i \in \{1, \dots, p\}$  and  $t = 0, 1, 2, \dots$ .

**Lemma 3.1.**  $\mathcal{L}(\mathbf{w}(t+1)) < \mathcal{L}(\mathbf{w}(t))$  ( $t = 0, 1, \dots$ ).

*Proof.* Since  $l$  is  $\beta$ -smooth, so is  $\mathcal{L}$ . Thus we have

$$\begin{aligned} & \mathcal{L}(\mathbf{w}(t+1)) \\ & \leq \mathcal{L}(\mathbf{w}(t)) + \nabla \mathcal{L}(\mathbf{w}(t)) (\mathbf{w}(t+1) - \mathbf{w}(t)) \\ & \quad + \frac{\beta}{2} \|\mathbf{w}(t+1) - \mathbf{w}(t)\|^2 \\ & = \mathcal{L}(\mathbf{w}(t)) - \eta \mathbf{g}(t)^T (\mathbf{h}(t) \odot \mathbf{g}(t)) \\ & \quad + \frac{\beta \eta^2}{2} \|\mathbf{h}(t) \odot \mathbf{g}(t)\|^2. \end{aligned}$$

Thus

$$\begin{aligned} & \mathcal{L}(\mathbf{w}(t)) - \mathcal{L}(\mathbf{w}(t+1)) \\ & \geq \eta \mathbf{g}(t)^T (\mathbf{h}(t) \odot \mathbf{g}(t)) - \frac{\beta \eta^2}{2} \|\mathbf{h}(t) \odot \mathbf{g}(t)\|^2 \\ & = \eta \sum_{i=1}^p \frac{g_i(t)^2}{\sqrt{S_i(t)} + \epsilon} - \frac{\beta \eta^2}{2} \sum_{i=1}^p \frac{g_i(t)^2}{S_i(t) + \epsilon} \\ & = \eta \sum_{i=1}^p \left( 1 - \frac{\beta \eta}{2\sqrt{S_i(t)} + \epsilon} \right) \frac{g_i(t)^2}{\sqrt{S_i(t)} + \epsilon} \\ & > 0. \end{aligned} \tag{1}$$

**Lemma 3.2.**  $\sum_{t=0}^{\infty} \|\mathbf{g}(t)\|^2 < \infty$ .

*Proof.* We use reduction of absurdity. Suppose

$$\sum_{t=1}^{\infty} \|\mathbf{g}(t)\|^2 = \infty.$$

Then there is some  $k \in \{1, \dots, p\}$  such that

$$\lim_{t \rightarrow \infty} S_k(t) = \sum_{t=1}^{\infty} g_k(t)^2 = \infty. \quad (2)$$

Thus we can find a time  $t_0$  such that, for all  $t > t_0$ ,

$$S_i(t) > \max(\beta\eta, 1).$$

Noting that positive series

$$\sum_{t=1}^{\infty} a_t, \quad \sum_{t=1}^{\infty} \frac{a_t}{a_1 + \dots + a_t + \epsilon}$$

converge or diverge simultaneously, so we obtain from (2)

$$\sum_{t=0}^{\infty} \frac{g_k(t)^2}{S_k(t) + \epsilon} = \infty.$$

Therefore,

$$\begin{aligned} & \sum_{t=0}^{\infty} \left(1 - \frac{\beta\eta}{2\sqrt{S_k(t) + \epsilon}}\right) \frac{g_k(\tau)^2}{\sqrt{S_k(t) + \epsilon}} \\ &= \sum_{t=0}^{t_0} \left(1 - \frac{\beta\eta}{2\sqrt{S_k(t) + \epsilon}}\right) \frac{g_k(\tau)^2}{\sqrt{S_k(t) + \epsilon}} \\ & \quad + \sum_{t>t_0} \left(1 - \frac{\beta\eta}{2\sqrt{S_k(t) + \epsilon}}\right) \frac{g_k(\tau)^2}{\sqrt{S_k(t) + \epsilon}} \\ &\geq C + \frac{1}{2} \sum_{t>t_0} \frac{g_k(t)^2}{\sqrt{S_k(t) + \epsilon}} \\ &\geq C + \frac{1}{2} \sum_{t>t_0} \frac{g_k(t)^2}{S_k(t) + \epsilon} \\ &= C + \infty = \infty, \end{aligned} \quad (3)$$

where the constant

$$C = \sum_{t=0}^{t_0} \left(1 - \frac{\beta\eta}{2\sqrt{S_k(t) + \epsilon}}\right) \frac{g_k(\tau)^2}{\sqrt{S_k(t) + \epsilon}}.$$

On the other hand, from (1) we have

$$\begin{aligned} & \sum_{\tau=0}^t \left(1 - \frac{\beta\eta}{2\sqrt{S_k(\tau) + \epsilon}}\right) \frac{g_k(\tau)^2}{\sqrt{S_k(\tau) + \epsilon}} \\ &\leq \sum_{\tau=0}^t \sum_{i=1}^p \left(1 - \frac{\beta\eta}{2\sqrt{S_i(\tau) + \epsilon}}\right) \frac{g_i(\tau)^2}{\sqrt{S_i(\tau) + \epsilon}} \\ &= \sum_{i=1}^p \left\{ \sum_{\tau=0}^t \left(1 - \frac{\beta\eta}{2\sqrt{S_i(\tau) + \epsilon}}\right) \frac{g_i(\tau)^2}{\sqrt{S_i(\tau) + \epsilon}} \right\} \\ &\leq \frac{1}{\eta} (\mathcal{L}(\mathbf{w}(0)) - \mathcal{L}(\mathbf{w}(t+1))) \leq \frac{\mathcal{L}(\mathbf{w}(0))}{\eta}, \end{aligned}$$

implying, for sufficiently small  $\eta$ ,

$$\sum_{t=0}^{\infty} \left(1 - \frac{\beta\eta}{2\sqrt{S_k(t) + \epsilon}}\right) \frac{g_k(\tau)^2}{\sqrt{S_k(t) + \epsilon}} \leq \frac{\mathcal{L}(\mathbf{w}(0))}{\eta},$$

which contradicts to (3).

**Lemma 3.3.** The following statements hold:

- (i)  $\|\mathbf{g}(t)\| \rightarrow 0$  ( $t \rightarrow \infty$ ).
- (ii)  $\|\mathbf{w}(t)\| \rightarrow \infty$  ( $t \rightarrow \infty$ ).
- (iii)  $\mathcal{L}(\mathbf{w}(t)) \rightarrow 0$  ( $t \rightarrow \infty$ ).
- (iv)  $\forall n, \lim_{t \rightarrow \infty} \mathbf{w}(t)^T \mathbf{x}_n = \infty$ .
- (v)  $\exists t_0, \forall t > t_0, \mathbf{w}(t)^T \mathbf{x}_n > 0$ .

*Proof.* Lemma 3.2 implies (i), which yields (ii).

To prove (iii), we use reduction to absurdity. Assume

$$\overline{\lim}_{t \rightarrow \infty} \mathcal{L}(\mathbf{w}(t)) = c > 0.$$

Then there exists an index  $m \in \{1, \dots, N\}$  such that

$$\overline{\lim}_{t \rightarrow \infty} l(\mathbf{w}(t)^T \mathbf{x}_m) \geq \frac{c}{N} > 0.$$

By Assumption 2, we have  $l(u) \rightarrow 0$  ( $u \rightarrow \infty$ ). Thus we can find a constant  $M > 0$  such that

$$\underline{\lim}_{t \rightarrow \infty} \mathbf{w}(t)^T \mathbf{x}_m \leq M,$$

which implies that there exists a sequence of times

$$t_1 < t_2 < t_3 < \dots$$

such that

$$\lim_{k \rightarrow \infty} \mathbf{w}(t_k)^T \mathbf{x}_m = \gamma \leq M.$$

Choose a vector  $\mathbf{w}_*$  such that  $\mathbf{w}_*^T \mathbf{x}_n > 0$  for all  $n \in \{1, \dots, N\}$ . Noting that  $-l' > 0$ , we have

$$\begin{aligned} -\mathbf{w}_*^T \mathbf{g}(t) &= -\sum_{n=1}^N l'(\mathbf{w}(t)^T \mathbf{x}_n) \mathbf{w}_*^T \mathbf{x}_n \\ &\geq l'(\mathbf{w}(t)^T \mathbf{x}_m) \mathbf{w}_*^T \mathbf{x}_m \end{aligned}$$

Thus

$$\begin{aligned} &\overline{\lim}_{k \rightarrow \infty} -\mathbf{w}_*^T \mathbf{g}(t_k) \\ &\geq \overline{\lim}_{k \rightarrow \infty} l'(\mathbf{w}(t_k)^T \mathbf{x}_m) \mathbf{w}_*^T \mathbf{x}_m \\ &= (\mathbf{w}_*^T \mathbf{x}_m) \lim_{k \rightarrow \infty} l'(\mathbf{w}(t_k)^T \mathbf{x}_m) \\ &= (\mathbf{w}_*^T \mathbf{x}_m) l'(\gamma) > 0. \end{aligned} \tag{4}$$

Note that

$$\|\mathbf{g}(t)\| \rightarrow 0 \quad (t \rightarrow \infty)$$

implies

$$-\mathbf{w}_*^T \mathbf{g}(t_k) \leq \|\mathbf{w}_*\| \|\mathbf{g}(t_k)\| \rightarrow 0 \quad (k \rightarrow \infty),$$

which contradicts to (4), meaning (iii) has to be true.

(iv) follows from (iii). (v) follows directly from (iv).

**Theorem 3.1.** The sequence  $\{\mathbf{h}(t)\}_{t=0}^\infty$  converges as  $t \rightarrow \infty$  to a vector

$$\mathbf{h}_\infty = (h_{\infty,1}, \dots, h_{\infty,p})$$

satisfying  $h_{\infty,i} > 0$  ( $i = 1, \dots, p$ ).

*Proof.* By Lemma 3.2  $\{h_i(t)\}_{t=0}^\infty$  is decreasing and has a lower bound

$$\frac{1}{\sqrt{S} + \epsilon} > 0,$$

where

$$S = \lim_{t \rightarrow \infty} S_i(t) \leq \sum_{t=0}^{\infty} \|\mathbf{g}(t)\|^2 < \infty,$$

then converges, for each  $i \in \{1, \dots, p\}$ .

**Lemma A.1.** Let  $\mathbf{a}, \mathbf{b} = (b_1, \dots, b_p) \in \mathbb{R}^p$ . Then the following relations hold.

- (i) Associativity.  $(\mathbf{a} \odot \mathbf{b}) \odot \mathbf{v} = \mathbf{a} \odot (\mathbf{b} \odot \mathbf{v})$ .
- (ii) Commutativity.  $\mathbf{a} \odot \mathbf{b} = \mathbf{b} \odot \mathbf{a}$ ;
- (iii) Distributivity.  $\mathbf{a} \odot (\mathbf{b} + \mathbf{c}) = \mathbf{a} \odot \mathbf{b} + \mathbf{a} \odot \mathbf{c}$ .
- (iv)  $\min_i |b_i| \|\mathbf{a}\| \leq \|\mathbf{b} \odot \mathbf{a}\| \leq \max_i |b_i| \|\mathbf{a}\|$ .

*Proof.* Obviously.

**Lemma 3.4.** The following statements hold:

- (i)  $\|\nabla \mathcal{L}_{ind}(t)\| \rightarrow 0$  ( $t \rightarrow \infty$ ).
- (ii)  $\|\mathbf{v}(t)\| \rightarrow \infty$  ( $t \rightarrow \infty$ ).
- (iii)  $\mathcal{L}_{ind}(\mathbf{v}(t)) \rightarrow 0$  ( $t \rightarrow \infty$ ).
- (iv)  $\forall n, \lim_{t \rightarrow \infty} \mathbf{v}(t)^T \boldsymbol{\xi}_n = \infty$ .
- (v)  $\exists t_0, \forall t > t_0, \mathbf{v}(t)^T \boldsymbol{\xi}_n > 0$ .

*Proof.* It directly follows from Lemma 3.3.

**Lemma A.2.** For  $t = 0, 1, 2 \dots$ ,

$$\boldsymbol{\delta}(t)^T \hat{\mathbf{u}} = \|P\boldsymbol{\delta}(t)\| \geq \frac{\|\boldsymbol{\delta}(t)\|}{\max_n \|\boldsymbol{\xi}_n\|},$$

where

$$\hat{\mathbf{u}} = \arg \min_{\mathbf{u}^T \boldsymbol{\xi}_n \geq 1, \forall n} \|\mathbf{u}\|^2.$$

*Proof.* From Assumption 2. we have  $-l'(\mathbf{v}^T \boldsymbol{\xi}_n) > 0$ . By the definition of  $\hat{\mathbf{u}}$  we have

$$\boldsymbol{\xi}_n^T \hat{\mathbf{u}} \geq 1 \quad (n = 1, \dots, N).$$

Thus

$$\boldsymbol{\delta}(t)^T \hat{\mathbf{u}} = -\eta \nabla \mathcal{L}_{ind}(\mathbf{v}(t))^T \hat{\mathbf{u}} = -\eta \sum_{n=1}^N l'(\mathbf{v}^T \boldsymbol{\xi}_n) \boldsymbol{\xi}_n^T \hat{\mathbf{u}} \geq -\eta \sum_{n=1}^N l'(\mathbf{v}^T \boldsymbol{\xi}_n) > 0.$$

Note that  $l' < 0$ . We have

$$\begin{aligned} \|\boldsymbol{\delta}(t)\| &= \left\| \eta \sum_{n=1}^N l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) \boldsymbol{\xi}_n \right\| \leq -\eta \sum_{n=1}^N l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) \|\boldsymbol{\xi}_n\| \\ &\leq \max_n \|\boldsymbol{\xi}_n\| \left( -\eta \sum_{n=1}^N l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) \right), \end{aligned}$$

or

$$-\eta \sum_{n=1}^N l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) \geq \frac{\|\boldsymbol{\delta}(t)\|}{\max_n \|\boldsymbol{\xi}_n\|}. \quad (5)$$

On the other hand,

$$\begin{aligned} P\boldsymbol{\delta}(t) &= -\eta P \sum_{n=1}^N l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) \boldsymbol{\xi}_n = -\eta \sum_{n=1}^N l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) P\boldsymbol{\xi}_n \\ &= -\eta \sum_{n=1}^N l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) (\boldsymbol{\xi}_n^T \hat{\mathbf{u}}) \hat{\mathbf{u}}. \end{aligned}$$

Noting  $\boldsymbol{\xi}_n^T \hat{\mathbf{u}} \geq 1$  ( $n \in \{1, \dots, N\}$ ), from (5) we obtain

$$\|P\boldsymbol{\delta}(t)\| = -\eta \sum_{n=1}^N l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) (\boldsymbol{\xi}_n^T \hat{\mathbf{u}}) \geq -\eta \sum_{n=1}^N l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) \geq \frac{\|\boldsymbol{\delta}(t)\|}{\max_n \|\boldsymbol{\xi}_n\|}.$$

**Lemma A.3.** For sufficiently large  $t$ ,

$$\frac{1}{2} \|\boldsymbol{\delta}(t)\| \leq \|\mathbf{d}(t)\| \leq \frac{3}{2} \|\boldsymbol{\delta}(t)\|, \quad (6)$$

$$\|P\mathbf{d}(t)\| \geq \frac{\|\mathbf{d}(t)\|}{4 \max_n \|\boldsymbol{\xi}_n\|}, \quad (7)$$

$$\mathbf{d}(t)^T \hat{\mathbf{u}} = \|P\mathbf{d}(t)\| > 0. \quad (8)$$

*Proof.* Let  $\boldsymbol{\beta}(t) = (\beta_1(t), \dots, \beta_p(t))^T$ . Noting that

$$\|\boldsymbol{\beta}(t) - \mathbf{1}\| \rightarrow 0 \quad (t \rightarrow \infty),$$

we can find some  $t_0$  such that for  $t \geq t_0$ ,

$$\frac{1}{2} \leq \min_i |\beta_i(t)| \leq \max_i |\beta_i(t)| \leq \frac{3}{2} \quad (9)$$

and

$$\max_i |\beta_i(t) - 1| < \frac{1}{2 \max_n \|\boldsymbol{\xi}_n\|}. \quad (10)$$

The inequality (6) follows directly from (9). On the other hand,

$$P\mathbf{d}(t) = P(\boldsymbol{\beta}(t) \odot \boldsymbol{\delta}(t)) = P\boldsymbol{\delta}(t) + P((\boldsymbol{\beta}(t) - \mathbf{1}) \odot \boldsymbol{\delta}(t))$$

By (10) we have

$$\|P((\boldsymbol{\beta}(t) - \mathbf{1}) \odot \boldsymbol{\delta}(t))\| \leq \|(\boldsymbol{\beta}(t) - \mathbf{1}) \odot \boldsymbol{\delta}(t)\| \leq \max_i |\beta_i(t) - 1| \|\boldsymbol{\delta}(t)\| \leq \frac{\|\boldsymbol{\delta}(t)\|}{2 \max_n \|\boldsymbol{\xi}_n\|}.$$

Hence

$$\begin{aligned} \|P\mathbf{d}(t)\| &= \|P\boldsymbol{\delta}(t) + P((\boldsymbol{\beta}(t) - \mathbf{1}) \odot \boldsymbol{\delta}(t))\| \\ &\geq \|P\boldsymbol{\delta}(t)\| - \|P((\boldsymbol{\beta}(t) - \mathbf{1}) \odot \boldsymbol{\delta}(t))\| \\ &\geq \frac{\|\boldsymbol{\delta}(t)\|}{\max_n \|\boldsymbol{\xi}_n\|} - \frac{\|\boldsymbol{\delta}(t)\|}{2 \max_n \|\boldsymbol{\xi}_n\|} = \frac{\|\boldsymbol{\delta}(t)\|}{2 \max_n \|\boldsymbol{\xi}_n\|}. \end{aligned}$$

Thus (7) follows from the left part of (6).

Noting that

$$\begin{aligned} \mathbf{d}(t)^T \hat{\mathbf{u}} &= \boldsymbol{\delta}(t)^T \hat{\mathbf{u}} + (\boldsymbol{\beta}(t) - \mathbf{1}) \odot \boldsymbol{\delta}(t)^T \hat{\mathbf{u}} \\ &\geq \boldsymbol{\delta}(t)^T \hat{\mathbf{u}} - |(\boldsymbol{\beta}(t) - \mathbf{1}) \odot \boldsymbol{\delta}(t)^T \hat{\mathbf{u}}| \\ &= \|P\boldsymbol{\delta}(t)\| - \|P((\boldsymbol{\beta}(t) - \mathbf{1}) \odot \boldsymbol{\delta}(t))\| \\ &\geq \frac{\|\boldsymbol{\delta}(t)\|}{\max_n \|\boldsymbol{\xi}_n\|} - \frac{\|\boldsymbol{\delta}(t)\|}{2 \max_n \|\boldsymbol{\xi}_n\|} \\ &= \frac{\|\boldsymbol{\delta}(t)\|}{2 \max_n \|\boldsymbol{\xi}_n\|} > 0, \end{aligned}$$

we obtain (8).

**Lemma A.4.** For sufficiently large  $t$ ,

$$\|P\mathbf{v}(t)\| \geq \frac{\|\mathbf{v}(t)\|}{8\max_n \|\boldsymbol{\xi}_n\|}.$$

*Proof.* By Lemma A.3 there exists some  $t_0$  such that for  $t \geq t_0$ ,

$$\|P\mathbf{d}(t)\| \geq \frac{\|\mathbf{d}(t)\|}{4\max_n \|\boldsymbol{\xi}_n\|}.$$

Note that  $\|\mathbf{v}(t)\| \rightarrow \infty$ , which implies

$$\|\mathbf{d}(t_0)\| + \dots + \|\mathbf{d}(t)\| \geq \|\mathbf{v}(t)\| - \|\mathbf{v}(t_0)\| \rightarrow \infty \quad (t \rightarrow \infty).$$

Thus there exists some  $t_1 > t_0$  such that for  $t > t_1$ ,

$$\|\mathbf{d}(t_0)\| + \dots + \|\mathbf{d}(t)\| > 2\|\mathbf{v}(t_0)\|,$$

Hence, meanwhile,

$$\begin{aligned} \|P\mathbf{v}(t)\| &= \|P\mathbf{v}(t_0) + P\mathbf{d}(t_0) + \dots + P\mathbf{d}(t-1)\| \\ &= \|P\mathbf{v}(t_0)\| + \|P\mathbf{d}(t_0)\| + \dots + \|P\mathbf{d}(t-1)\| \\ &\geq \frac{1}{4\max_n \|\boldsymbol{\xi}_n\|} (\|\mathbf{d}(t_0)\| + \dots + \|\mathbf{d}(t-1)\|) \\ &\geq \frac{1}{8\max_n \|\boldsymbol{\xi}_n\|} (\|\mathbf{v}(t_0)\| + \|\mathbf{d}(t_0)\| + \dots + \|\mathbf{d}(t-1)\|) \\ &\geq \frac{1}{8\max_n \|\boldsymbol{\xi}_n\|} \|\mathbf{v}(t_0) + \mathbf{d}(t_0) + \dots + \mathbf{d}(t-1)\| \\ &= \frac{\|\mathbf{v}(t)\|}{8\max_n \|\boldsymbol{\xi}_n\|}. \end{aligned}$$

**Lemma A.5.** Let

$$\mathcal{K} = \{n : \boldsymbol{\xi}_n^T \hat{\mathbf{u}} = 1\}.$$

Then there is a set of nonnegative numbers  $\{\alpha_n : n \in \mathcal{K}\}$  such that

$$\hat{\mathbf{u}} = \sum_{n \in \mathcal{K}} \alpha_n \boldsymbol{\xi}_n.$$

*Proof.* This is Lemma 12 in Appendix B of Soudry et al., [2018].

**Lemma 3.5.** Given  $\varepsilon > 0$ . Let  $a, b, c$  be positive numbers as defined in Assumption 3 in Section 2. If  $\|Q\mathbf{v}(t)\| > 2N(c+1)(ace\varepsilon)^{-1}$ , then for sufficiently large  $t$ ,

$$Q\mathbf{v}(t)^T \boldsymbol{\delta}(t) < \varepsilon \|Q\mathbf{v}(t)\| \|\boldsymbol{\delta}(t)\|.$$

*Proof.* Since for each  $n \in \{1, \dots, N\}$ ,

$$\mathbf{v}(t)^T \boldsymbol{\xi}_n \rightarrow \infty \quad (t \rightarrow \infty),$$

we have, for sufficiently large  $t$ ,

$$\begin{aligned} -l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) &= ce^{-a\mathbf{v}(t)^T \boldsymbol{\xi}_n} - r(\mathbf{v}(t)^T \boldsymbol{\xi}_n) \\ &\geq ce^{-a\mathbf{v}(t)^T \boldsymbol{\xi}_n} - e^{-(a+b)\mathbf{v}(t)^T \boldsymbol{\xi}_n} \\ &= e^{-a\mathbf{v}(t)^T \boldsymbol{\xi}_n} (c - e^{-b\mathbf{v}(t)^T \boldsymbol{\xi}_n}) \\ &= \frac{c}{2} e^{-a\mathbf{v}(t)^T \boldsymbol{\xi}_n}. \end{aligned} \tag{11}$$

Similarly, we can prove for sufficiently large  $t$ ,

$$-l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) \leq 2ce^{-a\mathbf{v}(t)^T \boldsymbol{\xi}_n}. \quad (12)$$

Denote

$$p(t) = \mathbf{v}(t)^T \hat{\mathbf{u}}, \quad \mathbf{q}(t) = Q\mathbf{v}(t).$$

Thus we have

$$\mathbf{v}(t) = p(t)\hat{\mathbf{u}} + \mathbf{q}(t).$$

Denote

$$u_n = \hat{\mathbf{u}}^T \boldsymbol{\xi}_n, \quad q_{n,t} = \mathbf{q}(t)^T \boldsymbol{\xi}_n.$$

We then have

$$\begin{aligned} & \mathbf{q}(t)^T \boldsymbol{\delta}(t) \\ &= -\eta \mathbf{q}(t)^T \sum_{n=1}^N l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) \boldsymbol{\xi}_n \\ &= -\eta \sum_{n=1}^N l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) \mathbf{q}(t)^T \boldsymbol{\xi}_n \\ &= -\eta \sum_{n=1}^N l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) q_{n,t} \\ &\leq -\eta \sum_{n: q_{n,t} > 0} l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) q_{n,t}. \end{aligned}$$

Applying (12) we obtain

$$\begin{aligned} \mathbf{q}(t)^T \boldsymbol{\delta}(t) &\leq \eta \sum_{n: q_{n,t} > 0} 2ce^{-a\mathbf{v}(t)^T \boldsymbol{\xi}_n} q_{n,t} \\ &= 2c\eta \sum_{n: q_{n,t} > 0} e^{-a(p(t)\hat{\mathbf{u}} + \mathbf{q}(t))^T \boldsymbol{\xi}_n} q_{n,t} \\ &= 2c\eta \sum_{n: q_{n,t} > 0} e^{-ap(t)u_n} e^{-aq_{n,t}} q_{n,t} \\ &\leq \frac{2c\eta}{ae} \sum_{n: q_{n,t} > 0} e^{-ap(t)u_n} \\ &\leq \frac{2c\eta N}{ae} e^{-ap(t)}. \end{aligned}$$

The last step is derived from  $u_n \geq 1$  for  $n \in \{1, \dots, N\}$ .

On the other hand, by Lemma A.5 there is a set of positive coefficients  $\{\alpha_n : n \in \mathcal{K}\}$ , where  $\mathcal{K} = \{n : u_n = 1\}$ , such that

$$\hat{\mathbf{u}} = \sum_{n \in \mathcal{K}} \alpha_n \boldsymbol{\xi}_n.$$

Thus

$$0 = \mathbf{q}(t)^T \hat{\mathbf{u}} = \sum_{n \in \mathcal{K}} \alpha_n \mathbf{q}(t)^T \boldsymbol{\xi}_n,$$

implying there is at least one index  $k \in \mathcal{K}$  such that

$$q_{t,k} = \mathbf{q}(t)^T \boldsymbol{\xi}_k \leq 0.$$

Hence

$$\begin{aligned}
\|P\boldsymbol{\delta}(t)\| &= \eta \left\| P \sum_{n=1}^N l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) \boldsymbol{\xi}_n \right\| \\
&= \eta \left\| \sum_{n=1}^N l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) P \boldsymbol{\xi}_n \right\| \\
&= \eta \left\| \sum_{n=1}^N l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) u_n \hat{\mathbf{u}} \right\| \\
&= -\eta \sum_{n=1}^N u_n l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) \\
&\geq -\eta \sum_{n=1}^N l'(\mathbf{v}(t)^T \boldsymbol{\xi}_n) \\
&> -\eta l'(\mathbf{v}(t)^T \boldsymbol{\xi}_k).
\end{aligned}$$

Noting that  $u_k \geq 1$ ,  $q_{t,k} \leq 0$ , and the estimation (11), we obtain

$$\begin{aligned}
\|P\boldsymbol{\delta}(t)\| &> -\eta l'(\mathbf{v}(t)^T \boldsymbol{\xi}_k) \\
&\geq \frac{c\eta}{2} e^{-a\mathbf{v}(t)^T \boldsymbol{\xi}_k} \\
&= \frac{c\eta}{2} e^{-ap(t)u_k} e^{-aq_{t,k}} \\
&\geq \frac{c\eta}{2} e^{-ap(t)}.
\end{aligned}$$

Thus

$$\begin{aligned}
\mathbf{q}(t)^T \boldsymbol{\delta}(t) &\leq \eta(c+1) \frac{N}{ae} e^{-ap(t)} \\
&\leq \frac{2N(c+1)}{ace} \|P\boldsymbol{\delta}(t)\| \\
&\leq \frac{2N(c+1)}{ace} \|\boldsymbol{\delta}(t)\| \\
&< \varepsilon \|\mathbf{q}(t)\| \|\boldsymbol{\delta}(t)\|,
\end{aligned}$$

for  $\|\mathbf{q}(t)\| > 2(ace\varepsilon)^{-1}N(c+1)$ .

**Lemma 3.6.** For any  $\varepsilon > 0$ , there exist  $R > 0$  such that for sufficiently large  $t$  and  $\|Q\mathbf{v}(t)\| \geq R$ ,

$$\|Q\mathbf{v}(t+1)\| - \|Q\mathbf{v}(t)\| \leq \varepsilon \|\mathbf{d}(t)\|.$$

*Proof.* Again we denote  $\mathbf{q}(t) = Q\mathbf{v}(t)$ . By Lemma 3.5 we can choose a number  $R > 0$  such that for sufficiently large  $t$  and  $\|\mathbf{q}(t)\| \geq R$ ,

$$\mathbf{q}(t)^T \boldsymbol{\delta}(t) < \frac{\varepsilon}{16} \|\mathbf{q}(t)\| \|\boldsymbol{\delta}(t)\| \quad (13)$$

and

$$\frac{1}{2} \|\boldsymbol{\delta}(t)\| \leq \|\mathbf{d}(t)\| \quad (14)$$

from (6). Noting

$$\|\mathbf{q}(t+1)\|^2 - \|\mathbf{q}(t)\|^2 = 2\mathbf{q}(t)^T Q\mathbf{d}(t) + \|Q\mathbf{d}(t)\|^2,$$

we have

$$\begin{aligned}
\|\mathbf{q}(t+1)\| - \|\mathbf{q}(t)\| &= \frac{\|\mathbf{q}(t+1)\|^2 - \|\mathbf{q}(t)\|^2}{\|\mathbf{q}(t+1)\| + \|\mathbf{q}(t)\|} \\
&= \frac{2\mathbf{q}(t)^T Q\mathbf{d}(t) + \|Q\mathbf{d}(t)\|^2}{\|\mathbf{q}(t+1)\| + \|\mathbf{q}(t)\|} \\
&\leq \frac{2\mathbf{q}(t)^T \mathbf{d}(t) + \|Q\mathbf{d}(t)\|^2}{\|\mathbf{q}(t)\|} \\
&= \frac{2\mathbf{q}(t)^T (\boldsymbol{\delta}(t) + (\boldsymbol{\beta}(t) - \mathbf{1}) \odot \boldsymbol{\delta}(t)) + \|Q\mathbf{d}(t)\|^2}{\|\mathbf{q}(t)\|} \\
&= \frac{2\mathbf{q}(t)^T \boldsymbol{\delta}(t)}{\|\mathbf{q}(t)\|} + \frac{2\mathbf{q}(t)^T (\boldsymbol{\beta}(t) - \mathbf{1}) \odot \boldsymbol{\delta}(t)}{\|\mathbf{q}(t)\|} + \frac{\|Q\mathbf{d}(t)\|^2}{\|\mathbf{q}(t)\|} \\
&\leq \frac{\varepsilon \|\boldsymbol{\delta}(t)\|}{8} + 2\|(\boldsymbol{\beta}(t) - \mathbf{1}) \odot \boldsymbol{\delta}(t)\| + \frac{\|d(t)\|^2}{R}
\end{aligned}$$

Since

$$\boldsymbol{\beta}(t) = (\beta_1(t), \dots, \beta_p(t))^T \rightarrow \mathbf{1} \quad (t \rightarrow \infty)$$

and

$$\|\mathbf{d}(t)\| \rightarrow 0 \quad (t \rightarrow \infty),$$

we can see that for sufficiently large  $t$ ,

$$\max_i |\beta_i(t) - 1| < \frac{\varepsilon}{8}$$

and

$$\|\mathbf{d}(t)\| < \frac{R\varepsilon}{8}.$$

Now we have

$$\begin{aligned}
\|(\boldsymbol{\beta}(t) - \mathbf{1}) \odot \boldsymbol{\delta}(t)\| &\leq \max_i |\beta_i(t) - 1| \|\boldsymbol{\delta}(t)\| \leq \frac{\varepsilon}{8} \|\boldsymbol{\delta}(t)\|, \\
\frac{\|d(t)\|^2}{R} &\leq \frac{\varepsilon}{8} \|\boldsymbol{\delta}(t)\|.
\end{aligned}$$

By (14), we obtain

$$\begin{aligned}
&\|\mathbf{q}(t+1)\| - \|\mathbf{q}(t)\| \\
&\leq \frac{\varepsilon \|\boldsymbol{\delta}(t)\|}{8} + 2\|(\boldsymbol{\beta}(t) - \mathbf{1}) \odot \boldsymbol{\delta}(t)\| + \frac{\|d(t)\|^2}{R} \\
&\leq \frac{\varepsilon \|\boldsymbol{\delta}(t)\|}{8} + \frac{\varepsilon \|\boldsymbol{\delta}(t)\|}{4} + \frac{\varepsilon \|\boldsymbol{\delta}(t)\|}{8} \\
&= \frac{\varepsilon \|\boldsymbol{\delta}(t)\|}{2} \leq \varepsilon \|\mathbf{d}(t)\|.
\end{aligned}$$

**Lemma 3.7.**

$$\lim_{t \rightarrow \infty} \frac{\mathbf{v}(t)}{\|\mathbf{v}(t)\|} = \hat{\mathbf{u}}. \quad (15)$$

*Proof.* Since  $\|\mathbf{d}(\tau)\| \rightarrow 0$  ( $\tau \rightarrow \infty$ ), we can find a time  $t_0$  such that for  $\tau \geq t_0$ ,

$$\|\mathbf{d}(\tau)\| \leq 1.$$

By Lemma A.3 we can find a time  $t_1 \geq t_0$  such that for  $\tau \geq t_1$ ,

$$\|\mathbf{d}(\tau)\| \leq \left(4 \max_n \|\boldsymbol{\xi}_n\|\right) \|P\mathbf{d}(\tau)\|. \quad (16)$$

Given  $\varepsilon > 0$ , by Lemma 3.6 we can choose  $R \geq 1$  and  $t_2 \geq t_1$  such that for  $\tau \geq t_2$  and  $\|\mathbf{q}(\tau)\| \geq R$ ,

$$\|\mathbf{q}(\tau+1)\| - \|\mathbf{q}(\tau)\| \leq \varepsilon \|\mathbf{d}(\tau)\|.$$

Since  $\|\mathbf{v}(\tau)\| \rightarrow \infty$  ( $\tau \rightarrow \infty$ ), we can choose  $t_3 \geq t_2$  such that for  $\tau \geq t_3$ ,

$$\|\mathbf{v}(\tau)\|^{-1}R < \varepsilon \quad (17)$$

and

$$\|\mathbf{v}(\tau)\|^{-1} \left( \|\mathbf{q}(t_2)\| + 4\varepsilon \max_n \|\boldsymbol{\xi}_n\| \|P\mathbf{v}(t_2)\| \right) < \varepsilon. \quad (18)$$

Now let  $t \geq t_3$ . To simplify notation we denote

$$\xi^* = \max_n \|\boldsymbol{\xi}_n\|.$$

**Case 1.** If  $\|\mathbf{q}(t)\| < R$ , then from (17) we directly obtain

$$\|\mathbf{v}(t)\|^{-1}\|\mathbf{q}(t)\| < \varepsilon. \quad (19)$$

**Case 2.** If for each  $\tau \in \{t_2, \dots, t\}$ ,  $\|\mathbf{q}(\tau)\| \geq R$ , then from (16),

$$\begin{aligned} \|\mathbf{q}(t)\| &= \|\mathbf{q}(t_2)\| + \sum_{\tau=t_2}^{t-1} (\|\mathbf{q}(\tau+1)\| - \|\mathbf{q}(\tau)\|) \\ &\leq \|\mathbf{q}(t_2)\| + \varepsilon (\|\mathbf{d}(t_2)\| + \dots + \|\mathbf{d}(t-1)\|) \\ &\leq \|\mathbf{q}(t_2)\| + 4\varepsilon \xi^* (\|P\mathbf{d}(t_2)\| + \dots + \|P\mathbf{d}(t-1)\|) \\ &= \|\mathbf{q}(t_2)\| + 4\varepsilon \xi^* (\|P\mathbf{d}(t_2)\| + \dots + P\mathbf{d}(t-1)\|) \\ &= \|\mathbf{q}(t_2)\| + 4\varepsilon \xi^* \|P(\mathbf{d}(t_2) + \dots + \mathbf{d}(t-1))\| \\ &= \|\mathbf{q}(t_2)\| + 4\varepsilon \xi^* \|P\mathbf{v}(t) - P\mathbf{v}(t_2)\| \\ &\leq \|\mathbf{q}(t_2)\| + 4\varepsilon \xi^* (\|P\mathbf{v}(t_2)\| + \|P\mathbf{v}(t)\|). \end{aligned}$$

From (18) we have

$$\begin{aligned} \|\mathbf{v}(t)\|^{-1}\|\mathbf{q}(t)\| &\leq \|\mathbf{v}(t)\|^{-1} (\|\mathbf{q}(t_2)\| + 4\varepsilon \xi^* \|P\mathbf{v}(t_2)\|) + 4\varepsilon \xi^* \|\mathbf{v}(t)\|^{-1}\|P\mathbf{v}(t)\| \\ &< \varepsilon + 4\varepsilon \xi^* = (1 + 4\xi^*)\varepsilon. \end{aligned} \quad (20)$$

**Case 3.** If  $\|\mathbf{q}(t)\| \geq R$  and there is a time  $t_* \in \{t_2, \dots, t-1\}$  such that

$$\|\mathbf{q}(t_*)\| < R,$$

then we can find the time  $t^* \in \{t_*, \dots, t-1\}$  such that

$$\|\mathbf{q}(t^*)\| < R$$

and for each  $\tau \in \{t^* + 1, \dots, t\}$ ,

$$\|\mathbf{q}(\tau)\| \geq R.$$

Thus we have

$$\begin{aligned} \|\mathbf{q}(t)\| &= \|\mathbf{q}(t^*)\| + (\|\mathbf{q}(t^*+1)\| - \|\mathbf{q}(t^*)\|) + \sum_{\tau=t^*+1}^{t-1} (\|\mathbf{q}(\tau+1)\| - \|\mathbf{q}(\tau)\|) \\ &< R + \|Q\mathbf{d}(t^*)\| + \varepsilon (\|\mathbf{d}(t^*+1)\| + \dots + \|\mathbf{d}(t-1)\|) \\ &\leq R + \|\mathbf{d}(t^*)\| + 4\varepsilon \xi^* (\|P\mathbf{d}(t^*+1)\| + \dots + \|P\mathbf{d}(t-1)\|) \\ &\leq R + \|\mathbf{d}(t^*)\| + 4\varepsilon \xi^* (\|P\mathbf{d}(t_2)\| + \dots + \|P\mathbf{d}(t-1)\|) \\ &= R + 1 + 4\varepsilon \xi^* (\|P\mathbf{d}(t_2)\| + \dots + P\mathbf{d}(t-1)\|) \\ &= 2R + 4\varepsilon \xi^* \|P\mathbf{v}(t) - P\mathbf{v}(t_2)\| \\ &\leq 2R + 4\varepsilon \xi^* (\|P\mathbf{v}(t_2)\| + \|P\mathbf{v}(t)\|). \end{aligned}$$

Noting (17) and (18), we obtain

$$\begin{aligned} \|\mathbf{v}(t)\|^{-1}\|\mathbf{q}(t)\| &\leq \|\mathbf{v}(t)\|^{-1} (2R + 4\varepsilon \xi^* \|P\mathbf{v}(t_2)\|) + 4\varepsilon \xi^* \|\mathbf{v}(t)\|^{-1}\|P\mathbf{v}(t)\| \\ &< 3\varepsilon + 4\varepsilon \xi^* = (3 + 4\xi^*)\varepsilon. \end{aligned} \quad (21)$$

Verifying (19), (20) and (21), we can see that, in any case, (21) is valid. Since  $\varepsilon$  can be any positive number, we have

$$\lim_{t \rightarrow \infty} \frac{\|\mathbf{q}(t)\|}{\|\mathbf{v}(t)\|} = 0.$$

Thus

$$\lim_{t \rightarrow \infty} \frac{\|P\mathbf{v}(t)\|}{\|\mathbf{v}(t)\|} = 1, \quad \lim_{t \rightarrow \infty} \frac{\mathbf{q}(t)}{\|\mathbf{v}(t)\|} = \mathbf{0}.$$

Therefore,

$$\lim_{t \rightarrow \infty} \frac{\mathbf{v}(t)}{\|\mathbf{v}(t)\|} = \lim_{t \rightarrow \infty} \frac{P\mathbf{v}(t) + \mathbf{q}(t)}{\|\mathbf{v}(t)\|} = \lim_{t \rightarrow \infty} \frac{P\mathbf{v}(t)}{\|\mathbf{v}(t)\|} = \lim_{t \rightarrow \infty} \frac{\|P\mathbf{v}(t)\|}{\|\mathbf{v}(t)\|} \hat{\mathbf{u}} = \hat{\mathbf{u}}.$$

**Theorem 3.2.** AdaGrad iterates

$$\mathbf{w}(t+1) = \mathbf{w}(t) - \eta \mathbf{h}(t) \odot \mathbf{g}(t), \quad t = 0, 1, 2, \dots, \quad (22)$$

has an asymptotic direction:

$$\lim_{t \rightarrow \infty} \frac{\mathbf{w}(t)}{\|\mathbf{w}(t)\|} = \frac{\tilde{\mathbf{w}}}{\|\tilde{\mathbf{w}}\|},$$

where

$$\tilde{\mathbf{w}} = \arg \min_{\mathbf{w}^T \mathbf{x}_n \geq 1, \forall n} \left\| \mathbf{h}_\infty^{-1/2} \odot \mathbf{w} \right\|^2. \quad (23)$$

*Proof.* By hypothesis

$$\begin{aligned} \left\| \mathbf{h}_\infty^{1/2} \odot \mathbf{w}_\infty \right\|^2 &= \min_{\mathbf{w}^T \mathbf{x}_n \geq 1, \forall n} \left\| \mathbf{h}_\infty^{1/2} \odot \mathbf{w} \right\|^2 = \min_{(\mathbf{h}_\infty^{1/2} \odot \mathbf{u})^T \mathbf{x}_n \geq 1, \forall n} \|\mathbf{u}\|^2 \\ &= \min_{\mathbf{u}^T (\mathbf{h}_\infty^{1/2} \odot \mathbf{x}_n) \geq 1, \forall n} \|\mathbf{u}\|^2 = \min_{\mathbf{u}^T \boldsymbol{\xi}_n \geq 1, \forall n} \|\mathbf{u}\|^2. \end{aligned}$$

Noting that both

$$\hat{\mathbf{u}} = \arg \min_{\mathbf{u}^T \boldsymbol{\xi}_n \geq 1, \forall n} \|\mathbf{u}\|^2.$$

and  $\mathbf{w}_\infty$  are unique, we must have  $\hat{\mathbf{u}} = \mathbf{h}_\infty^{-1/2} \odot \mathbf{w}_\infty$ , or

$$\mathbf{w}_\infty = \mathbf{h}_\infty^{1/2} \odot \hat{\mathbf{u}}.$$

From Lemma 3.7 and the relation

$$\mathbf{v}(t) = \mathbf{h}_\infty^{-1/2} \odot \mathbf{w}(t) \quad (t = 0, 1, 2, \dots),$$

we obtain

$$\mathbf{w}_\infty = \mathbf{h}_\infty^{1/2} \odot \lim_{t \rightarrow \infty} \frac{\mathbf{v}(t)}{\|\mathbf{v}(t)\|} = \lim_{t \rightarrow \infty} \frac{\mathbf{h}_\infty^{1/2} \odot \mathbf{v}(t)}{\|\mathbf{v}(t)\|} = \lim_{t \rightarrow \infty} \frac{\mathbf{w}(t)}{\|\mathbf{v}(t)\|}.$$

Thus

$$\lim_{t \rightarrow \infty} \frac{\mathbf{w}(t)}{\|\mathbf{w}(t)\|} = \lim_{t \rightarrow \infty} \frac{\|\mathbf{v}(t)\|}{\|\mathbf{w}(t)\|} \cdot \lim_{t \rightarrow \infty} \frac{\mathbf{w}(t)}{\|\mathbf{v}(t)\|} = \frac{\mathbf{w}_\infty}{\|\mathbf{w}_\infty\|}.$$

**Proposition 3.1.** Let  $\mathbf{a} = (a_1, \dots, a_p)^T$  be a vector satisfying  $\mathbf{a}^T \mathbf{x}_n \geq 1$  ( $n = 1, \dots, N$ ) and  $a_1 \cdots a_p \neq 0$ . Suppose that  $\mathbf{w} = (w_1, \dots, w_p)^T$  satisfies  $\mathbf{w}^T \mathbf{x}_n \geq 1$  ( $n = 1, \dots, N$ ) and

$$a_i (w_i - a_i) \geq 0 \quad (i = 1, \dots, p). \quad (24)$$

Then for any  $\mathbf{b} = (b_1, \dots, b_p)^T$  such that  $b_1 \cdots b_p \neq 0$ ,

$$\arg \min_{\mathbf{w}^T \mathbf{x}_n \geq 1, \forall n} \|\mathbf{b} \odot \mathbf{w}\|^2 = \arg \min_{\mathbf{w}^T \mathbf{x}_n \geq 1, \forall n} \|\mathbf{w}\|^2 = \mathbf{a},$$

and therefore the asymptotic directions of AdaGrad (22) and GD

$$\mathbf{w}_G(t+1) = \mathbf{w}_G(t) - \eta \nabla \mathcal{L}(\mathbf{w}_G(t)) \quad (t = 0, 1, 2, \dots), \quad (25)$$

are equal.

*Proof.* Without any loss of generality we may assume  $a_i > 0$  ( $i = 1, \dots, p$ ). Then (24) implies

$$w_i \geq a_i > 0 \quad (i = 1, \dots, p),$$

and thus

$$\|\mathbf{b} \odot \mathbf{w}\|^2 = b_1^2 w_1^2 + \dots + b_p^2 w_p^2 \geq b_1^2 a_1^2 + \dots + b_p^2 a_p^2.$$

Hence

$$\mathbf{a} = \arg \min_{\mathbf{w} \in F} \|\mathbf{b} \odot \mathbf{w}\|^2 = \arg \min_{\mathbf{w}^T \mathbf{x}_n \geq 1, \forall n} \|\mathbf{b} \odot \mathbf{w}\|^2.$$

By taking  $\mathbf{b} = \mathbf{h}_\infty^{1/2}$ , we get  $\tilde{\mathbf{w}} = \hat{\mathbf{w}}$ , where

$$\hat{\mathbf{w}} = \arg \min_{\mathbf{w}^T \mathbf{x}_n \geq 1, \forall n} \|\mathbf{w}\|^2.$$

Thus the asymptotic direction of GD iterates (25),  $\hat{\mathbf{w}}/\|\hat{\mathbf{w}}\|$ , is equal to  $\tilde{\mathbf{w}}/\|\tilde{\mathbf{w}}\|$ , which is the asymptotic direction of AdaGrad iterates (22).

**Lemma A.6.** Suppose  $N \geq p$  and the  $p \times N$ -matrix  $\mathbf{X} = [\mathbf{x}_1, \dots, \mathbf{x}_N]$ , where

$$\mathbf{x}_n = (x_{n,1}, \dots, x_{n,p})^T \quad (n = 1, \dots, N),$$

satisfies the following conditions:

(i) For  $n = 1, \dots, p$ ,

$$x_{n,i} \begin{cases} > 0, & \text{for } i = n, \\ < 0, & \text{for } i \neq n. \end{cases}$$

(ii) The  $p \times p$ -matrix  $\mathbf{X}_p = [\mathbf{x}_1, \dots, \mathbf{x}_p]$  is nonsingular.

(iii) The unique solution  $\mathbf{a} = (a_1, \dots, a_p)^T$  of the linear system in  $\mathbf{w}$

$$\mathbf{x}_n^T \mathbf{w} = 1 \quad (n = 1, \dots, p). \quad (26)$$

satisfies  $a_i > 0$  ( $i = 1, \dots, p$ ).

Furthermore, suppose a vector  $\mathbf{u} = (u_1, \dots, u_p)^T$  satisfies

$$\mathbf{x}_n^T \mathbf{u} \geq 1 \quad (n = 1, \dots, N), \quad (27)$$

then

$$u_i \geq a_i \quad (i = 1, \dots, p). \quad (28)$$

*Proof.* For  $n = 1$ , we set

$$h_1 = \frac{1}{x_{1,1}} (\mathbf{x}_1^T \mathbf{u} - 1) \geq 0$$

and

$$\bar{u}_1 = u_1 - h_1 \leq u_1.$$

Denote  $\mathbf{u}_1 = (\bar{u}_1, u_2, \dots, u_p)^T$ . Then

$$\mathbf{x}_1^T \mathbf{u}_1 = x_{1,1} \bar{u}_1 + x_{1,2} u_2 + \dots + x_{1,n} u_n = \mathbf{x}_1^T \mathbf{u} - (\mathbf{x}_1^T \mathbf{u} - 1) = 1.$$

Since  $x_{2,1} < 0$  and  $\bar{u}_1 \leq u_1$ , we have

$$\begin{aligned} \mathbf{x}_2^T \mathbf{u}_1 &= x_{2,1} \bar{u}_1 + x_{2,2} u_2 + \dots + x_{2,n} u_n \\ &\geq x_{2,1} u_1 + x_{2,2} u_2 + \dots + x_{2,n} u_n \\ &\geq \mathbf{x}_2^T \mathbf{u} \geq 1. \end{aligned}$$

Now we set

$$h_2 = \frac{1}{x_{2,2}} (\mathbf{x}_2^T \mathbf{u}_1 - 1) \geq 0$$

and

$$\bar{u}_2 = u_2 - h_2 \leq u_2.$$

Denote  $\mathbf{u}_2 = (\bar{u}_1, \bar{u}_2, u_3, \dots, u_p)^T$ . Then

$$\begin{aligned} \mathbf{x}_2^T \mathbf{u}_2 &= x_{2,1}\bar{u}_1 + x_{2,2}\bar{u}_2 + x_{2,3}u_3 + \dots + x_{2,n}u_n \\ &= \mathbf{x}_2^T \mathbf{u}_1 - (\mathbf{x}_2^T \mathbf{u}_1 - 1) = 1. \end{aligned}$$

Sequentially, we can define  $\bar{u}_1, \dots, \bar{u}_p$ , such that

$$\bar{u}_n \leq u_n \quad (n = 1, \dots, p). \quad (29)$$

Denote  $\mathbf{u}_p = (\bar{u}_1, \dots, \bar{u}_p)^T$ . Then

$$\mathbf{x}_n^T \mathbf{u}_p = 1 \quad (n = 1, \dots, p).$$

Noting that  $\mathbf{a}$  is the unique solution of (26), we must have  $\mathbf{u}_p = \mathbf{a}$ , or

$$\bar{u}_n = a_n \quad (n = 1, \dots, p),$$

which combined with (29) yields (28).

**Proposition 3.2.** Suppose  $N \geq p$  and  $\mathbf{X} = [\mathbf{x}_1, \dots, \mathbf{x}_N] \in \mathbb{R}^{p \times N}$  is sampled from any distribution whose density function is nonzero almost everywhere. Then with a positive probability the asymptotic directions of AdaGrad (22) and GD (25) are equal.

*Proof.* Let  $\Pi_{n,i} : \mathbb{R}^{p \times N} \rightarrow \mathbb{R}$  be the projections defined as

$$\Pi_{n,i}(\mathbf{X}) = x_{n,i} \quad (n, i = 1, \dots, p)$$

and let  $G_{n,i} \subset \mathbb{R}^{p \times N}$  defined as

$$G_{n,n} = \{\mathbf{X} \mid \Pi_{n,n}(\mathbf{X}) > 0\}, \quad G_{n,k} = \{\mathbf{X} \mid \Pi_{n,k}(\mathbf{X}) < 0\} \quad (n, k = 1, \dots, p; k \neq n).$$

Then  $G_{n,i}$ 's are open, for all the projections are continuous.

Let  $\mathbf{\Pi} : \mathbb{R}^{p \times N} \rightarrow \mathbb{R}^{p \times p}$  be the projection defined as

$$\mathbf{\Pi}(\mathbf{X}) = [\mathbf{x}_1, \dots, \mathbf{x}_p]$$

and let  $D \subset \mathbb{R}^{p \times N}$  defined as

$$D = \{\mathbf{X} \mid \det(\mathbf{\Pi}(\mathbf{X})) \neq 0\}.$$

Since both  $\mathbf{\Pi}$  and  $\det(\cdot)$  are continuous,  $D$  is open.

Let  $\Pi_i : \mathbb{R}^p \rightarrow \mathbb{R}$  be the projections defined as

$$\Pi_i(w_1, \dots, w_p) = w_i \quad (i = 1, \dots, p)$$

and let  $A \subset \mathbb{R}^{p \times N}$  defined as

$$A = \left\{ \mathbf{X} \mid \mathbf{X} \in D, \Pi_i \left( \left( \mathbf{\Pi}(\mathbf{X})^T \right)^{-1} \mathbf{1} \right) > 0 \quad (i = 1, \dots, p) \right\},$$

where  $\mathbf{1} = (1, \dots, 1)^T \in \mathbb{R}^p$ . Since all  $\Pi_i$  are continuous,  $A$  is open.

Clearly, for a matrix  $\mathbf{X} \in \mathbb{R}^{p \times N}$ , we have:

- 1) the condition (i) in Lemma A.6 holds, if and only if  $\mathbf{X} \in G_{n,i}$  ( $n, i = 1, \dots, p$ );
- 2) the condition (ii) in Lemma A.6 holds, if and only if  $\mathbf{X} \in D$ ;
- 3) the condition (iii) in Lemma A.6 holds, if and only if  $\mathbf{X} \in A$ .

Suppose  $P$  is a distribution over  $\mathbb{R}^{p \times N}$  and the density function of  $P$  is nonzero almost everywhere. Let  $\mathcal{S}$  be the set of all  $p \times N$ -matrices  $\mathbf{X}$  satisfying conditions (i), (ii) and (iii). Then

$$\mathcal{S} = \left( \bigcap_{n,i=1}^p G_{n,i} \right) \cap D \cap A$$

is open in  $\mathbb{R}^{p \times N}$ . Thus  $P(\mathcal{S}) > 0$ .

For any  $\mathbf{X} \in \mathcal{S}$ , if  $\mathbf{w} = (w_1, \dots, w_p)$  satisfies  $\mathbf{x}_n^T \mathbf{w} \geq 1$  ( $n = 1, \dots, N$ ), then by Lemma A.6 we have

$$w_i \geq a_i, \text{ or } w_i - a_i \geq 0 \quad (i = 1, \dots, p),$$

where  $\mathbf{a} = (a_1, \dots, a_p)^T$  is the unique solution of (26) with

$$a_i > 0 \quad (i = 1, \dots, p).$$

Thus

$$\mathbf{w} = \mathbf{a} + (\mathbf{w} - \mathbf{a}) \in \left\{ \mathbf{a} + \mathbf{u} : \mathbf{u} = (u_1, \dots, u_p)^T \text{ such that } a_i u_i \geq 0 \quad (i = 1, \dots, p) \right\},$$

and the required conclusion follows from Proposition 3.1.