

## 9. Supplementary Material

### 9.1. Proof of Lemma 6.1

Note that the update rule (24) can be written as

$$\mathbf{Z}^{k+1} := \mathbf{Z}^k + \mathbf{W}\mathbf{Z}^k - \tilde{\mathbf{W}}\mathbf{Z}^{k-1} - \alpha(\hat{\mathcal{B}}^k(\mathbf{Z}^{k+1}) - \hat{\mathcal{B}}^{k-1}(\mathbf{Z}^k)), \quad (47)$$

from the definition of  $\tilde{\mathbf{W}}$ . To prove the first part of the lemma, by summing (47) from  $k = 1$  to  $t$  and (25), one has

$$\mathbf{Z}^{t+1} = (\mathbf{W} - \tilde{\mathbf{W}}) \sum_{k=0}^t \mathbf{Z}^k + \tilde{\mathbf{W}}\mathbf{Z}^t - \alpha\hat{\mathcal{B}}^t(\mathbf{Z}^{t+1}). \quad (48)$$

From the definition of  $\mathbf{U}$  and  $\mathbf{Q}^t$  and the identity  $\mathbf{I} = 2\tilde{\mathbf{W}} - \mathbf{W}$ , we have

$$\alpha\hat{\mathcal{B}}^t(\mathbf{Z}^{t+1}) = \tilde{\mathbf{W}}(\mathbf{Z}^t - \mathbf{Z}^{t+1}) - \mathbf{U}\mathbf{Q}^{t+1}. \quad (49)$$

By subtracting the optimality condition (15), we have the result.

From first part, we have

$$\begin{aligned} & \langle \mathbf{Z}^{t+1} - \mathbf{Z}^*, \alpha[\mathcal{B}(\mathbf{Z}^*) - \hat{\mathcal{B}}^t(\mathbf{Z}^{t+1})] \rangle \\ &= \langle \mathbf{Z}^{t+1} - \mathbf{Z}^*, -\tilde{\mathbf{W}}(\mathbf{Z}^t - \mathbf{Z}^{t+1}) + \mathbf{U}(\mathbf{Q}^{t+1} - \mathbf{Q}^*) \rangle \\ &= \langle \mathbf{Z}^{t+1} - \mathbf{Z}^*, \mathbf{Z}^{t+1} - \mathbf{Z}^t \rangle_{\tilde{\mathbf{W}}} + \langle \mathbf{Z}^{t+1} - \mathbf{Z}^*, \mathbf{U}(\mathbf{Q}^{t+1} - \mathbf{Q}^*) \rangle \\ &= \langle \mathbf{Z}^{t+1} - \mathbf{Z}^*, \mathbf{Z}^{t+1} - \mathbf{Z}^t \rangle_{\tilde{\mathbf{W}}} + \langle \mathbf{Q}^{t+1} - \mathbf{Q}^t, \mathbf{Q}^{t+1} - \mathbf{Q}^* \rangle, \end{aligned} \quad (50)$$

where the last equality uses the definition of  $\mathbf{Q}^t$  and that  $\mathbf{U}\mathbf{Z}^* = \mathbf{0}$ . By applying the generalized Law of cosines  $2\langle a, b \rangle = \|a\|^2 + \|b\|^2 - \|a - b\|^2$  with  $a = \mathbf{X}^{t+1} - \mathbf{X}^*$  and  $b = \mathbf{X}^{t+1} - \mathbf{X}^t$ , we have the second part.

### 9.2. Proof of Lemma 6.2

We have  $T^{t+1} \geq \frac{1}{L}S^{t+1}$  from the definition of cocoerciveness. Expanding the definition of  $\hat{\mathcal{B}}^t(\mathbf{Z}^{t+1})$ , we have

$$\begin{aligned} & \mathbb{E} \langle \mathbf{Z}^{t+1} - \mathbf{Z}^*, \mathcal{B}(\mathbf{Z}^*) - \hat{\mathcal{B}}^t(\mathbf{Z}^{t+1}) \rangle \\ &= \sum_{n=1}^N -\mathbb{E}_{i_n^t} \langle \mathbf{z}_{n,i_n^t}^{t+1} - \mathbf{z}^*, \mathcal{B}_{n,i_n^t}(\mathbf{z}_{n,i_n^t}^{t+1}) - \mathcal{B}_{n,i_n^t}(\mathbf{z}^*) \rangle \\ & \quad + \mathbb{E}_{i_n^t} \langle \mathbf{z}_{n,i_n^t}^{t+1} - \mathbf{z}^*, [\mathcal{B}_{n,i_n^t}(\mathbf{y}_{n,i_n^t}^t) - \mathcal{B}_{n,i_n^t}(\mathbf{z}^*)] - [\frac{1}{q} \sum_{i=1}^q \mathcal{B}_{n,i}(\mathbf{y}_{n,i}^t) - \mathcal{B}_n(\mathbf{z}^*)] \rangle. \end{aligned} \quad (51)$$

The first term is exactly  $-\frac{1}{2}T^{t+1}$ , and is bounded by  $-\frac{1}{2}T^{t+1} \leq -\frac{\theta}{2L}S^{t+1} - \frac{1-\theta}{2}T^{t+1}$  for  $0 \leq \theta \leq 1$ . Since

$$\mathbb{E}_{i_n^t} \{ [\mathcal{B}_{n,i_n^t}(\mathbf{y}_{n,i_n^t}^t) - \mathcal{B}_{n,i_n^t}(\mathbf{z}^*)] - [\frac{1}{q} \sum_{i=1}^q \mathcal{B}_{n,i}(\mathbf{y}_{n,i}^t) - \mathcal{B}_n(\mathbf{z}^*)] \} = \mathbf{0}, \quad (52)$$

and  $\mathbf{z}_n^t$  is independent of  $i_n^t$ , we have

$$\mathbb{E}_{i_n^t} \langle \mathbf{z}_n^t - \mathbf{z}^*, [\mathcal{B}_{n,i_n^t}(\mathbf{y}_{n,i_n^t}^t) - \mathcal{B}_{n,i_n^t}(\mathbf{z}^*)] - [\frac{1}{q} \sum_{i=1}^q \mathcal{B}_{n,i}(\mathbf{y}_{n,i}^t) - \mathcal{B}_n(\mathbf{z}^*)] \rangle = 0. \quad (53)$$

We bound the second term by

$$\begin{aligned}
 & \sum_{n=1}^N \mathbb{E}_{i_n^t} \langle \mathbf{z}_{n,i_n^t}^{t+1} - \mathbf{z}^*, [\mathcal{B}_{n,i_n^t}(\mathbf{y}_{n,i_n^t}^t) - \mathcal{B}_{n,i_n^t}(\mathbf{z}^*)] - [\frac{1}{q} \sum_{i=1}^q \mathcal{B}_{n,i}(\mathbf{y}_{n,i}^t) - \mathcal{B}_n(\mathbf{z}^*)] \rangle \\
 &= \sum_{n=1}^N \mathbb{E}_{i_n^t} \langle \mathbf{z}_{n,i_n^t}^{t+1} - \mathbf{z}_n^t, [\mathcal{B}_{n,i_n^t}(\mathbf{y}_{n,i_n^t}^t) - \mathcal{B}_{n,i_n^t}(\mathbf{z}^*)] - [\frac{1}{q} \sum_{i=1}^q \mathcal{B}_{n,i}(\mathbf{y}_{n,i}^t) - \mathcal{B}_n(\mathbf{z}^*)] \rangle \\
 &\leq \sum_{n=1}^N \frac{\eta}{2} \mathbb{E}_{i_n^t} \| [\mathcal{B}_{n,i_n^t}(\mathbf{y}_{n,i_n^t}^t) - \mathcal{B}_{n,i_n^t}(\mathbf{z}^*)] - [\frac{1}{q} \sum_{i=1}^q \mathcal{B}_{n,i}(\mathbf{y}_{n,i}^t) - \mathcal{B}_n(\mathbf{z}^*)] \|^2 + \frac{1}{2\eta} \mathbb{E}_{i_n^t} \|\mathbf{z}_{n,i_n^t}^{t+1} - \mathbf{z}_n^t\|^2 \\
 &\leq \sum_{n=1}^N \frac{\eta}{2} \mathbb{E}_{i_n^t} \|\mathcal{B}_{n,i_n^t}(\mathbf{y}_{n,i_n^t}^t) - \mathcal{B}_{n,i_n^t}(\mathbf{z}^*)\|^2 + \frac{1}{2\eta} \mathbb{E}_{i_n^t} \|\mathbf{z}_{n,i_n^t}^{t+1} - \mathbf{z}_n^t\|^2 \\
 &= \frac{1}{2\eta} \mathbb{E} \|\mathbf{Z}^{t+1} - \mathbf{Z}^t\|^2 + \frac{\eta}{4} D^t, \tag{54}
 \end{aligned}$$

where we use  $\langle a, b \rangle \leq \frac{1}{2\eta} \|a\|^2 + \frac{\eta}{2} \|b\|^2$  in first inequality and  $\|a - \mathbb{E}a\|^2 \leq \|a\|^2$  in the second one.

### 9.3. Proof of Lemma 6.3

From the definition of  $\hat{\mathcal{B}}^t(\mathbf{Z}^{t+1})$ , on node  $n$ , we have

$$\hat{\mathcal{B}}_n^t(\mathbf{z}_n^{t+1}) - \mathcal{B}_n(\mathbf{z}^*) = [\mathcal{B}_{n,i_n^t}(\mathbf{z}_{n,i_n^t}^{t+1}) - \mathcal{B}_{n,i_n^t}(\mathbf{z}^*)] - [\mathcal{B}_{n,i_n^t}(\mathbf{y}_{n,i_n^t}^t) - \mathcal{B}_{n,i_n^t}(\mathbf{z}^*)] + [\frac{1}{q} \sum_{i=1}^q \mathcal{B}_{n,i}(\mathbf{y}_{n,i}^t) - \mathcal{B}_n(\mathbf{z}^*)]. \tag{55}$$

Using  $\|a + b\|^2 \leq 2\|a\|^2 + 2\|b\|^2$ , we have

$$\begin{aligned}
 & \mathbb{E} \|\hat{\mathcal{B}}^t(\mathbf{Z}^{t+1}) - \mathcal{B}(\mathbf{Z}^*)\|^2 \\
 &\leq \sum_{n=1}^N 2\mathbb{E}_{i_n^t} \|\mathcal{B}_{n,i_n^t}(\mathbf{z}_{n,i_n^t}^{t+1}) - \mathcal{B}_{n,i_n^t}(\mathbf{z}^*)\|^2 + 2\mathbb{E}_{i_n^t} \| [\mathcal{B}_{n,i_n^t}(\mathbf{y}_{n,i_n^t}^t) - \mathcal{B}_{n,i_n^t}(\mathbf{z}^*)] - [\frac{1}{q} \sum_{i=1}^q \mathcal{B}_{n,i}(\mathbf{y}_{n,i}^t) - \mathcal{B}_n(\mathbf{z}^*)] \|^2 \\
 &\leq S^{t+1} + D^t, \tag{56}
 \end{aligned}$$

where the last inequality uses the definition of  $D^t$  and  $S^{t+1}$  and  $\|a - \mathbb{E}a\|^2 \leq \|a\|^2$ .

### 9.4. Proof of Lemma 6.4

Expand  $\|\mathbf{X}^t - \mathbf{X}^*\|_M^2$  by the definition of  $\mathbf{X}^t$  and  $\|\cdot\|_M$  and suppose  $\mathbf{Z}^{t+1}$  and  $\mathbf{Q}^{t+1}$  are generated from some fixed  $i_n^t, n \in [N]$ . Using  $\|a + b\|^2 \leq 2\|a\|^2 + 2\|b\|^2$ , we have

$$\begin{aligned}
 \|\mathbf{X}^t - \mathbf{X}^*\|_M^2 &= \|\mathbf{Z}^t - \mathbf{Z}^*\|_{\tilde{\mathbf{W}}}^2 + \|\mathbf{Q}^t - \mathbf{Q}^*\|^2 \\
 &\leq 2\|\mathbf{Z}^{t+1} - \mathbf{Z}^t\|_{\tilde{\mathbf{W}}}^2 + 2\|\mathbf{Z}^{t+1} - \mathbf{Z}^*\|_{\tilde{\mathbf{W}}}^2 + 2\|\mathbf{Q}^{t+1} - \mathbf{Q}^t\|^2 + 2\|\mathbf{Q}^{t+1} - \mathbf{Q}^*\|^2. \tag{57}
 \end{aligned}$$

We now bound the second term and last term. Using

$$\|\mathbf{Z}^{t+1} - \mathbf{Z}^*\|_{\tilde{\mathbf{W}}}^2 \leq \|\mathbf{Z}^{t+1} - \mathbf{Z}^*\|^2 \tag{58}$$

since  $\tilde{\mathbf{W}} \preceq I$ , and the  $\mu$ -strongly monotonicity of  $\mathcal{B}_{n,i_n^t}$ , we have

$$\|\mathbf{Z}^{t+1} - \mathbf{Z}^*\|_{\tilde{\mathbf{W}}}^2 \leq \frac{1}{\mu} \sum_{n=1}^N \langle \mathbf{z}_{n,i_n^t}^{t+1} - \mathbf{z}^*, \mathcal{B}_{n,i_n^t}(\mathbf{z}_{n,i_n^t}^{t+1}) - \mathcal{B}_{n,i_n^t}(\mathbf{z}^*) \rangle. \tag{59}$$

From the construction of  $\mathbf{Q}^{t+1}$  and  $\mathbf{Q}^*$ , every column of  $\mathbf{Q}^{t+1} - \mathbf{Q}^*$  is in  $\text{span}(U)$ , thus we have

$$\gamma \|\mathbf{Q}^{t+1} - \mathbf{Q}^*\|^2 \leq \|U(\mathbf{Q}^{t+1} - \mathbf{Q}^*)\|^2, \tag{60}$$

where  $\gamma$  is the smallest nonzero singular value of  $U^2 = \tilde{\mathbf{W}} - W$ . From Lemma 6.1, we write

$$\begin{aligned} \|U(\mathbf{Q}^{t+1} - \mathbf{Q}^*)\|^2 &= \|\alpha[\hat{\mathcal{B}}^t(\mathbf{Z}^{t+1}) - \mathcal{B}(\mathbf{Z}^*)] + \tilde{\mathbf{W}}(\mathbf{Z}^{t+1} - \mathbf{Z}^t)\|^2 \\ &\leq 2\alpha^2\|\hat{\mathcal{B}}^t(\mathbf{Z}^{t+1}) - \mathcal{B}(\mathbf{Z}^*)\|^2 + 2\|\mathbf{Z}^{t+1} - \mathbf{Z}^t\|_{\tilde{\mathbf{W}}}^2. \end{aligned} \quad (61)$$

Substituting these two upper bounds into (57), we have

$$\begin{aligned} \|\mathbf{X}^t - \mathbf{X}^*\|_M^2 &\leq (2 + \frac{4}{\gamma})\|\mathbf{Z}^{t+1} - \mathbf{Z}^t\|_{\tilde{\mathbf{W}}}^2 + 2\|\mathbf{Q}^{t+1} - \mathbf{Q}^t\|^2 + \frac{2}{\mu} \sum_{n=1}^N \langle \mathbf{z}_{n,i_n}^{t+1} - \mathbf{z}^*, \mathcal{B}_{n,i_n}(\mathbf{z}_{n,i_n}^{t+1}) - \mathcal{B}_{n,i_n}(\mathbf{z}^*) \rangle \\ &\quad + \frac{4\alpha^2}{\gamma} \|\hat{\mathcal{B}}^t(\mathbf{Z}^{t+1}) - \mathcal{B}(\mathbf{Z}^*)\|^2. \end{aligned} \quad (62)$$

Taking expectation and using Lemma 6.3, we have the result.

### 9.5. Proof of Theorem 6.1

From Lemma 6.1 and 6.2, we have

$$\begin{aligned} &\mathbb{E}\|\mathbf{X}^{t+1} - \mathbf{X}^*\|_M^2 - \|\mathbf{X}^t - \mathbf{X}^*\|_M^2 + \mathbb{E}\|\mathbf{X}^{t+1} - \mathbf{X}^t\|_M^2 \\ &= 2\alpha\mathbb{E}\langle \mathbf{Z}^{t+1} - \mathbf{Z}^*, \mathcal{B}(\mathbf{Z}^*) - \hat{\mathcal{B}}^t(\mathbf{Z}^{t+1}) \rangle \\ &\leq \frac{\alpha}{\eta}\mathbb{E}\|\mathbf{Z}^{t+1} - \mathbf{Z}^t\|^2 + \frac{\eta\alpha}{2}D^t - \frac{\theta\alpha}{L}S^{t+1} - (1-\theta)\alpha T^{t+1}. \end{aligned} \quad (63)$$

Also for  $D^{t+1}$ , we have

$$\begin{aligned} \mathbb{E}D^{t+1} &= \sum_{n=1}^N \frac{2}{q} \sum_{i=1}^q \mathbb{E}_{i_n} \|\mathcal{B}_{n,i}(\mathbf{y}_{n,i}^{t+1}) - \mathcal{B}_{n,i}(\mathbf{z}^*)\|^2 \\ &= \sum_{n=1}^N \frac{2}{q} \sum_{i=1}^q \left\{ \frac{1}{q} \|\mathcal{B}_{n,i}(\mathbf{z}_{n,i}^{t+1}) - \mathcal{B}_{n,i}(\mathbf{z}^*)\|^2 + (1 - \frac{1}{q}) \|\mathcal{B}_{n,i}(\mathbf{y}_{n,i}^t) - \mathcal{B}_{n,i}(\mathbf{z}^*)\|^2 \right\} \\ &= (1 - \frac{1}{q})D^t + \frac{1}{q}S^{t+1}. \end{aligned} \quad (64)$$

By adding  $cD^{t+1}$  and rearranging terms, we have

$$\begin{aligned} \mathbb{E}[\|\mathbf{X}^{t+1} - \mathbf{X}^*\|_M^2 + cD^{t+1}] &\leq \|\mathbf{X}^t - \mathbf{X}^*\|_M^2 - \mathbb{E}\|\mathbf{X}^{t+1} - \mathbf{X}^t\|_M^2 + (1 - \frac{1}{q})cD^t + \frac{c}{q}S^{t+1} \\ &\quad + \frac{\alpha}{\eta}\mathbb{E}\|\mathbf{Z}^{t+1} - \mathbf{Z}^t\|^2 + \frac{\eta\alpha}{2}D^t - \frac{\theta\alpha}{L}S^{t+1} - (1-\theta)\alpha T^{t+1}. \end{aligned} \quad (65)$$

If we further have

$$\begin{aligned} (1-\delta)[\|\mathbf{X}^t - \mathbf{X}^*\|_M^2 + cD^t] &\geq \|\mathbf{X}^t - \mathbf{X}^*\|_M^2 - \mathbb{E}\|\mathbf{X}^{t+1} - \mathbf{X}^t\|_M^2 + (1 - \frac{1}{q})cD^t + \frac{c}{q}S^{t+1} \\ &\quad + \frac{\alpha}{\eta}\mathbb{E}\|\mathbf{Z}^{t+1} - \mathbf{Z}^t\|^2 + \frac{\eta\alpha}{2}D^t - \frac{\theta\alpha}{L}S^{t+1} - (1-\theta)\alpha T^{t+1}, \end{aligned} \quad (66)$$

then we have the result. The above inequality is equivalent to

$$\begin{aligned} &(\frac{c}{q} - c\delta - \frac{\alpha\eta}{2})D^t + (\frac{\alpha\theta}{L} - \frac{c}{q})S^{t+1} + \alpha(1-\theta)T^{t+1} \\ &\geq \underbrace{\delta\|\mathbf{X}^t - \mathbf{X}^*\|_M^2 - \|\mathbf{X}^{t+1} - \mathbf{X}^t\|_M^2 + \frac{\alpha}{\eta}\mathbb{E}\|\mathbf{Z}^{t+1} - \mathbf{Z}^t\|^2}_{\Lambda}, \end{aligned} \quad (67)$$

and hence a sufficient condition is that an upper bound of the right hand side is less than the left hand side.

To bound  $\Lambda$ , using Lemma 6.4 for the first term, the definition of  $\|\mathbf{X}^{t+1} - \mathbf{X}^t\|_{\mathbf{M}}^2$  for the second term, and

$$\frac{1}{2}\|\mathbf{Z}^{t+1} - \mathbf{Z}^t\|^2 \leq \|\mathbf{Z}^{t+1} - \mathbf{Z}^t\|_{\tilde{\mathbf{W}}}^2 \quad (68)$$

for the third term since  $\frac{1}{2}I \preceq \tilde{\mathbf{W}}$ , we have

$$\begin{aligned} \Lambda \leq & \delta \left[ \left(2 + \frac{4}{\gamma}\right) \mathbb{E}\|\mathbf{Z}^{t+1} - \mathbf{Z}^t\|_{\tilde{\mathbf{W}}}^2 + \frac{1}{\mu} T^{t+1} + 2\mathbb{E}\|\mathbf{Q}^{t+1} - \mathbf{Q}^t\|^2 + \frac{4\alpha^2}{\gamma} (S^{t+1} + D^t) \right] \\ & - \mathbb{E}\|\mathbf{Z}^{t+1} - \mathbf{Z}^t\|_{\tilde{\mathbf{W}}}^2 - \mathbb{E}\|\mathbf{Q}^{t+1} - \mathbf{Q}^t\|^2 + \frac{2\alpha}{\eta} \mathbb{E}\|\mathbf{Z}^{t+1} - \mathbf{Z}^t\|_{\tilde{\mathbf{W}}}^2. \end{aligned} \quad (69)$$

Uniting like terms gives us the following sufficient condition for Theorem 6.1 to stand:

$$\begin{aligned} & \left(\frac{c}{q} - c\delta - \frac{\alpha\eta}{2} - \frac{4\delta\alpha^2}{\gamma}\right) D^t + \left(\frac{\alpha\theta}{L} - \frac{c}{q} - \frac{4\delta\alpha^2}{\gamma}\right) S^{t+1} + \left(\alpha(1-\theta) - \frac{\delta}{\mu}\right) T^{t+1} \\ & + (1-2\delta)\mathbb{E}\|\mathbf{Q}^{t+1} - \mathbf{Q}^t\|^2 + \left(1 - \left(2 + \frac{4}{\gamma}\right)\delta - \frac{2\alpha}{\eta}\right) \mathbb{E}\|\mathbf{Z}^{t+1} - \mathbf{Z}^t\|_{\tilde{\mathbf{W}}}^2 \geq 0. \end{aligned} \quad (70)$$

Since every term in the above inequality is nonnegative, this inequality holds when every bracket is nonnegative. Let

$$\alpha = \frac{\tau}{L}, \eta = 4\alpha, \theta = \frac{1}{2}, c = \frac{mq}{L^2}, \quad (71)$$

where  $\tau$  and  $m$  are constant to be set. The non-negativity of of the first two brackets equivalents to

$$\begin{cases} c\left(\frac{1}{3q} - \delta\right) + \frac{2m}{3L^2} - \frac{2\tau^2}{L^2} - \frac{\delta}{\gamma} \frac{4\tau^2}{L^2} \geq 0 \\ \frac{\tau}{2L^2} - \frac{m}{L^2} - \frac{\delta}{\gamma} \frac{4\tau^2}{L^2} \geq 0 \end{cases} \quad (72)$$

Taking  $\tau = \frac{1}{24}$ ,  $m = \frac{1}{96}$ ,  $\delta \leq \min\left\{\frac{\gamma}{12}, \frac{\mu}{48L}, \frac{1}{3q}, \frac{1}{4}\right\}$ , we have the result.

## 9.6. Resolvent of Logistic Regression

In Logistic Regression, each component operator  $\mathcal{B}_{n,i}$  is defined as  $\mathcal{B}_{n,i}(\mathbf{z}) = \frac{-y_{n,i}}{1 + \exp(y_{n,i} \mathbf{a}_{n,i}^\top \mathbf{z})} \mathbf{a}_{n,i}$ , where  $\mathbf{a}_{n,i} \in \mathbb{R}^d$  is the feature vector of a sample and  $y_{n,i} \in \{-1, +1\}$  is its class label. The resolvent,  $\mathcal{J}_{\alpha\mathcal{B}_{n,i}}(\mathbf{z})$ , does not admit a closed form solution, but can be computed efficiently by the following newton iteration: let  $a_0 = 0$ ,  $b = \mathbf{a}_{n,i}^\top \mathbf{z}$

$$e_k = \frac{-y_{n,i}}{1 + \exp(y_{n,i} a_k)} \quad \text{and} \quad a_{k+1} = a_k - \frac{\alpha e_k + a_k - b}{1 - \alpha y_{n,i} e_k - \alpha e_k^2}. \quad (73)$$

When the iterate converges, the resolvent is obtain by

$$\mathcal{J}_{\alpha\mathcal{B}_{n,i}}(\mathbf{z}) = \mathbf{z} - (b - a_k) \mathbf{a}_{n,i}. \quad (74)$$

In our experiments, 20 newton iteration is sufficient for DSBA.

## 9.7. Resolvent of AUC maximization

In the  $\ell_2$ -relaxed AUC maximization, the variable  $\mathbf{z} \in \mathbb{R}^{d+3}$  is a  $d+3$ -dimensional augmented vector, where  $d$  is the dimension of the dataset. For simplicity, we decompose  $\mathbf{z}$  as  $\mathbf{z} = [\mathbf{w}^\top; a; b; \theta]$  with  $\mathbf{w} \in \mathbb{R}^d$ ,  $a \in \mathbb{R}$ ,  $b \in \mathbb{R}$ ,  $\theta \in \mathbb{R}$ . For a positive sample, i.e.  $y_{n,i} = +1$ , the component operator  $\mathcal{B}_{n,i}$  is then defined as

$$\mathcal{B}_{n,i}(\mathbf{z}) = \begin{bmatrix} 2(1-p)((\mathbf{a}_{n,i}^\top \mathbf{w} - a) - (1+\theta)) \mathbf{a}_{n,i} \\ -2(1-p)(\mathbf{a}_{n,i}^\top \mathbf{w} - a) \\ 0 \\ 2p(1-p)\theta + 2(1-p) \mathbf{a}_{n,i}^\top \mathbf{w} \end{bmatrix} \quad (75)$$

and for a negative sample, i.e.  $y_{n,i} = -1$

$$\mathcal{B}_{n,i}(\mathbf{z}) = \begin{bmatrix} 2p((\mathbf{a}_{n,i}^\top \mathbf{w} - b) + (1 + \theta))\mathbf{a}_{n,i} \\ 0 \\ -2p(\mathbf{a}_{n,i}^\top \mathbf{w} - b) \\ 2p(1 - p)\theta - 2p\mathbf{a}_{n,i}^\top \mathbf{w} \end{bmatrix} \quad (76)$$

where  $p = \frac{\text{\#positive samples}}{\text{\#samples}}$  is the positive ratio of the dataset. Similar to RR, the resolvent of  $\mathcal{B}_{n,i}$  also admits a closed form solution, which we now derive. For a positive sample, define

$$\mathbf{A}^+ = \begin{bmatrix} 1 + 2(1 - p)\alpha & -2(1 - p)\alpha & 0 & -2(1 - p)\alpha \\ -2(1 - p)\alpha & 1 + 2(1 - p)\alpha & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 2(1 - p)\alpha & 0 & 0 & 1 + 2p(1 - p)\alpha \end{bmatrix} \quad (77)$$

and

$$\mathbf{b}^+ = \begin{bmatrix} \mathbf{a}_{n,i}^\top \mathbf{w} + 2(1 - p)\alpha \\ a \\ b \\ \theta \end{bmatrix}. \quad (78)$$

Let  $\mathbf{b}_r^+ = (\mathbf{A}^+)^{-1}\mathbf{b}^+ \in \mathbb{R}^4$  and decompose it as  $\mathbf{b}_r^+ = [z_r^+; a_r^+; b_r^+; \theta_r^+]$ . The resolvent is obtain as

$$\mathcal{J}_{\alpha\mathcal{B}_{n,i}}(\mathbf{z}) = \mathbf{z}_r^+ = \begin{bmatrix} [\mathbf{w} - 2(1 - p)\alpha[(z_r^+ - a) - (1 + \theta)]\mathbf{a}_{n,i}] \\ a_r^+ \\ b_r^+ \\ \theta_r^+ \end{bmatrix} \quad (79)$$

We can do the similar derivation for a negative sample. Define

$$\mathbf{A}^- = \begin{bmatrix} 1 + 2p\alpha & 0 & -2p\alpha & 2p\alpha \\ 0 & 1 & 0 & 0 \\ -2p\alpha & 0 & 1 + 2p\alpha & 0 \\ -2p\alpha & 0 & 0 & 1 + 2p(1 - p)\alpha \end{bmatrix} \quad (80)$$

and

$$\mathbf{b}^- = \begin{bmatrix} \mathbf{a}_{n,i}^\top \mathbf{w} - 2p\alpha \\ a \\ b \\ \theta \end{bmatrix} \quad (81)$$

Let  $\mathbf{b}_r^- = (\mathbf{A}^-)^{-1}\mathbf{b}^- \in \mathbb{R}^4$  and decompose it as  $\mathbf{b}_r^- = [z_r^-; a_r^-; b_r^-; \theta_r^-]$ . The resolvent is obtain as

$$\mathcal{J}_{\alpha\mathcal{B}_{n,i}}(\mathbf{z}) = \mathbf{z}_r^- = \begin{bmatrix} [\mathbf{w} - 2p\alpha[(z_r^- - b) - (1 + \theta)]\mathbf{a}_{n,i}] \\ a_r^- \\ b_r^- \\ \theta_r^- \end{bmatrix}. \quad (82)$$