

Appendix A. Proofs

Appendix A.1. Proof of Lemma 3.2

Proof. Given a quadratic surface \mathcal{S} denoted by (10), for any point $\mathbf{x} \in \mathcal{S}$, recall the definitions of $\hat{\mathbf{n}}(\mathbf{x})$, $\gamma(\mathbf{x})$, $\gamma^+(\mathbf{x})$, $\gamma^-(\mathbf{x})$, \mathbf{x}^+ and \mathbf{x}^- in Section 3.2. By (11), $Q(\mathbf{x}^+) = 1$ and $Q(\mathbf{x}^-) = -1$, which are equivalent to

$$\begin{aligned} \frac{1}{2}(\mathbf{x} + \gamma^+(\mathbf{x})\hat{\mathbf{n}}(\mathbf{x}))^T \mathbf{W}(\mathbf{x} + \gamma^+(\mathbf{x})\hat{\mathbf{n}}(\mathbf{x})) + \mathbf{b}^T(\mathbf{x} + \gamma^+(\mathbf{x})\hat{\mathbf{n}}(\mathbf{x})) + c - 1 &= 0 \\ \frac{1}{2}(\mathbf{x} - \gamma^-(\mathbf{x})\hat{\mathbf{n}}(\mathbf{x}))^T \mathbf{W}(\mathbf{x} - \gamma^-(\mathbf{x})\hat{\mathbf{n}}(\mathbf{x})) + \mathbf{b}^T(\mathbf{x} - \gamma^-(\mathbf{x})\hat{\mathbf{n}}(\mathbf{x})) + c + 1 &= 0 \end{aligned} \quad (\text{A.1})$$

With $Q(\mathbf{x}) = \frac{1}{2}\mathbf{x}^T \mathbf{W} \mathbf{x} + \mathbf{b}^T \mathbf{x} + c = 0$, (A.1) can be simplified as the following:

$$\begin{aligned} \frac{1}{2}\gamma^+(\mathbf{x})^2 \hat{\mathbf{n}}(\mathbf{x})^T \mathbf{W} \hat{\mathbf{n}}(\mathbf{x}) + \gamma^+(\mathbf{x}) \hat{\mathbf{n}}(\mathbf{x})^T (\mathbf{W} \mathbf{x} + \mathbf{b}) - 1 &= 0 \\ \frac{1}{2}\gamma^-(\mathbf{x})^2 \hat{\mathbf{n}}(\mathbf{x})^T \mathbf{W} \hat{\mathbf{n}}(\mathbf{x}) - \gamma^-(\mathbf{x}) \hat{\mathbf{n}}(\mathbf{x})^T (\mathbf{W} \mathbf{x} + \mathbf{b}) + 1 &= 0 \end{aligned} \quad (\text{A.2})$$

Notice that (A.2) are second order equations with respect to $\gamma^+(\mathbf{x})$ and $\gamma^-(\mathbf{x})$, respectively. Therefore, we will be able to solve out the explicit solutions as the following:

$$\begin{aligned} \gamma^+(\mathbf{x}) &= \frac{-\hat{\mathbf{n}}(\mathbf{x})^T (\mathbf{W} \mathbf{x} + \mathbf{b}) \pm \sqrt{[\hat{\mathbf{n}}(\mathbf{x})^T (\mathbf{W} \mathbf{x} + \mathbf{b})]^2 + 2\hat{\mathbf{n}}(\mathbf{x})^T \mathbf{W} \hat{\mathbf{n}}(\mathbf{x})}}{\hat{\mathbf{n}}(\mathbf{x})^T \mathbf{W} \hat{\mathbf{n}}(\mathbf{x})} \\ \gamma^-(\mathbf{x}) &= \frac{\hat{\mathbf{n}}(\mathbf{x})^T (\mathbf{W} \mathbf{x} + \mathbf{b}) \pm \sqrt{[\hat{\mathbf{n}}(\mathbf{x})^T (\mathbf{W} \mathbf{x} + \mathbf{b})]^2 - 2\hat{\mathbf{n}}(\mathbf{x})^T \mathbf{W} \hat{\mathbf{n}}(\mathbf{x})}}{\hat{\mathbf{n}}(\mathbf{x})^T \mathbf{W} \hat{\mathbf{n}}(\mathbf{x})} \end{aligned}$$

By the definition, we have $\hat{\mathbf{n}}(\mathbf{x})^T (\mathbf{W} \mathbf{x} + \mathbf{b}) = \|\mathbf{W} \mathbf{x} + \mathbf{b}\|$. Then the above equations can be simplified as the following:

$$\gamma^+(\mathbf{x}) = \frac{-\|\mathbf{W} \mathbf{x} + \mathbf{b}\| \pm \sqrt{\|\mathbf{W} \mathbf{x} + \mathbf{b}\|^2 + 2\hat{\mathbf{n}}(\mathbf{x})^T \mathbf{W} \hat{\mathbf{n}}(\mathbf{x})}}{\hat{\mathbf{n}}(\mathbf{x})^T \mathbf{W} \hat{\mathbf{n}}(\mathbf{x})}, \quad \gamma^-(\mathbf{x}) = \frac{\|\mathbf{W} \mathbf{x} + \mathbf{b}\| \pm \sqrt{\|\mathbf{W} \mathbf{x} + \mathbf{b}\|^2 - 2\hat{\mathbf{n}}(\mathbf{x})^T \mathbf{W} \hat{\mathbf{n}}(\mathbf{x})}}{\hat{\mathbf{n}}(\mathbf{x})^T \mathbf{W} \hat{\mathbf{n}}(\mathbf{x})}$$

By eliminating two useless roots, we have the explicit solutions of $\gamma^+(\mathbf{x})$ and $\gamma^-(\mathbf{x})$.

$$\begin{aligned} \gamma^+(\mathbf{x}) &= \frac{-\|\mathbf{W} \mathbf{x} + \mathbf{b}\| + \sqrt{\|\mathbf{W} \mathbf{x} + \mathbf{b}\|^2 + 2\hat{\mathbf{n}}(\mathbf{x})^T \mathbf{W} \hat{\mathbf{n}}(\mathbf{x})}}{\hat{\mathbf{n}}(\mathbf{x})^T \mathbf{W} \hat{\mathbf{n}}(\mathbf{x})} \\ \gamma^-(\mathbf{x}) &= \frac{\|\mathbf{W} \mathbf{x} + \mathbf{b}\| - \sqrt{\|\mathbf{W} \mathbf{x} + \mathbf{b}\|^2 - 2\hat{\mathbf{n}}(\mathbf{x})^T \mathbf{W} \hat{\mathbf{n}}(\mathbf{x})}}{\hat{\mathbf{n}}(\mathbf{x})^T \mathbf{W} \hat{\mathbf{n}}(\mathbf{x})} \end{aligned} \quad (\text{A.3})$$

By (12), there exists an orthonormal matrix $\mathbf{U} \in \mathbb{R}^{n \times n}$ such that $\mathbf{W} = \mathbf{U} \mathbf{\Sigma} \mathbf{U}^T$, where $\mathbf{\Sigma}$ is a diagonal matrix of the singular values of \mathbf{W} . Recall that the singular values of \mathbf{W} are in a decreasing order: $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r \geq \sigma_{r+1} = \dots = \sigma_n = 0$. Denote $\mathbf{U} = [\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n]$. Then $\{\mathbf{u}_i \in \mathbb{R}^n\}_{1 \leq i \leq n}$ forms an orthonormal basis on \mathbb{R}^n . Hence, there exists $\boldsymbol{\alpha}(\mathbf{x}) = [\alpha_1(\mathbf{x}), \alpha_2(\mathbf{x}), \dots, \alpha_n(\mathbf{x})]^T \in \mathbb{R}^n$ such that

$$\mathbf{W} \mathbf{x} + \mathbf{b} = \sum_{i=1}^n \alpha_i(\mathbf{x}) \mathbf{u}_i = \mathbf{U} \boldsymbol{\alpha}(\mathbf{x}). \quad (\text{A.4})$$

Taking (A.4) into (A.3) and we have

$$\gamma^+(\mathbf{x}) = \frac{-\|\mathbf{U} \boldsymbol{\alpha}(\mathbf{x})\| + \sqrt{\|\mathbf{U} \boldsymbol{\alpha}(\mathbf{x})\|^2 + 2 \frac{\boldsymbol{\alpha}(\mathbf{x})^T \mathbf{\Sigma} \boldsymbol{\alpha}(\mathbf{x})}{\boldsymbol{\alpha}(\mathbf{x})^T \boldsymbol{\alpha}(\mathbf{x})}}}{\frac{\boldsymbol{\alpha}(\mathbf{x})^T \mathbf{\Sigma} \boldsymbol{\alpha}(\mathbf{x})}{\boldsymbol{\alpha}(\mathbf{x})^T \boldsymbol{\alpha}(\mathbf{x})}}, \quad \gamma^-(\mathbf{x}) = \frac{\|\mathbf{U} \boldsymbol{\alpha}(\mathbf{x})\| - \sqrt{\|\mathbf{U} \boldsymbol{\alpha}(\mathbf{x})\|^2 - 2 \frac{\boldsymbol{\alpha}(\mathbf{x})^T \mathbf{\Sigma} \boldsymbol{\alpha}(\mathbf{x})}{\boldsymbol{\alpha}(\mathbf{x})^T \boldsymbol{\alpha}(\mathbf{x})}}}{\frac{\boldsymbol{\alpha}(\mathbf{x})^T \mathbf{\Sigma} \boldsymbol{\alpha}(\mathbf{x})}{\boldsymbol{\alpha}(\mathbf{x})^T \boldsymbol{\alpha}(\mathbf{x})}}$$

Notice that $\frac{\alpha(\mathbf{x})^T \Sigma \alpha(\mathbf{x})}{\alpha(\mathbf{x})^T \alpha(\mathbf{x})}$ is the Rayleigh quotient of Σ at $\alpha(\mathbf{x})$. Denote $\frac{\alpha(\mathbf{x})^T \Sigma \alpha(\mathbf{x})}{\alpha(\mathbf{x})^T \alpha(\mathbf{x})} = R(\Sigma, \alpha(\mathbf{x}))$. By Parseval's identity, $\|\mathbf{U}\alpha(\mathbf{x})\|_2^2 = \|\alpha(\mathbf{x})\|_2^2$. Hence, the G-margin at \mathbf{x} can be written as

$$\gamma(\mathbf{x}) = \gamma^+(\mathbf{x}) + \gamma^-(\mathbf{x}) = \frac{\sqrt{\|\alpha(\mathbf{x})\|^2 + 2R(\Sigma, \alpha(\mathbf{x}))} - \sqrt{\|\alpha(\mathbf{x})\|^2 - 2R(\Sigma, \alpha(\mathbf{x}))}}{R(\Sigma, \alpha(\mathbf{x}))} \quad (\text{A.5})$$

Notice that inequality $\sqrt{x} - \sqrt{y} \leq \sqrt{x-y}$ holds for any $x \geq y \geq 0$. Therefore, we have the following inequality.

$$\frac{1}{\gamma(\mathbf{x})} = \frac{1}{\gamma^+(\mathbf{x}) + \gamma^-(\mathbf{x})} \geq \frac{\sqrt{R(\Sigma, \alpha(\mathbf{x}))}}{2}. \quad (\text{A.6})$$

Since Σ is known when \mathcal{S} is given, we proved Lemma 3.2. □

Appendix A.2. Proof of theorem 4.1

Proof. Assume $(\mathbf{v}^*, \mathbf{b}^*, q^*, \zeta^*)$ and $(\hat{\mathbf{v}}, \hat{\mathbf{b}}, \hat{q}, \hat{\zeta})$ are both optimal solutions to problem (DWPSVM''). For a convex program, its optimal solution set is convex. In other words, $(\forall \alpha \in (0, 1)) \alpha(\mathbf{v}^*, \mathbf{b}^*, q^*, \zeta^*) + (1 - \alpha)(\hat{\mathbf{v}}, \hat{\mathbf{b}}, \hat{q}, \hat{\zeta})$ is optimal as well. Denote the optimal value as \bar{z} .

Define function $p : \mathbb{R}^{\frac{l(l+1)+n(n+1)}{2} + N} \rightarrow \mathbb{R}$, such that

$$p(\mathbf{v}, \mathbf{b}, \zeta) \triangleq \frac{1}{2} \mathbf{v}^T \mathbf{H} \mathbf{v} + \frac{1}{2} \|\mathbf{b}\|_2^2 + C \sum_{i=1}^N \zeta_i. \quad (\text{A.7})$$

which leads to

$$\begin{aligned} \bar{z} &= \frac{1}{2} (\alpha \mathbf{v}^* + (1 - \alpha) \hat{\mathbf{v}})^T \mathbf{H} (\alpha \mathbf{v}^* + (1 - \alpha) \hat{\mathbf{v}}) + \frac{1}{2} (\alpha \mathbf{b}^* + (1 - \alpha) \hat{\mathbf{b}})^T (\alpha \mathbf{b}^* + (1 - \alpha) \hat{\mathbf{b}}) + C \sum_{i=1}^N (\alpha \zeta_i^* + (1 - \alpha) \hat{\zeta}_i) \\ &= \frac{\alpha^2}{2} (\mathbf{v}^{*T} \mathbf{H} \mathbf{v}^* + \mathbf{b}^{*T} \mathbf{b}^*) + \frac{(1 - \alpha)^2}{2} (\hat{\mathbf{v}}^T \mathbf{H} \hat{\mathbf{v}} + \hat{\mathbf{b}}^T \hat{\mathbf{b}}) + \alpha(1 - \alpha) (\mathbf{v}^{*T} \mathbf{H} \hat{\mathbf{v}} + \mathbf{b}^{*T} \hat{\mathbf{b}}) + C \sum_{i=1}^N (\alpha \zeta_i^* + (1 - \alpha) \hat{\zeta}_i) \\ &= \alpha p(\mathbf{v}^*, \mathbf{b}^*, \zeta^*) + (1 - \alpha) p(\hat{\mathbf{v}}, \hat{\mathbf{b}}, \hat{\zeta}) + \alpha(1 - \alpha) ((\mathbf{v}^* - \hat{\mathbf{v}})^T \mathbf{H} (\mathbf{v}^* - \hat{\mathbf{v}}) + (\mathbf{b}^* - \hat{\mathbf{b}})^T (\mathbf{b}^* - \hat{\mathbf{b}})). \end{aligned}$$

Since $\bar{z} = p(\mathbf{v}^*, \mathbf{b}^*, \zeta^*) = p(\hat{\mathbf{v}}, \hat{\mathbf{b}}, \hat{\zeta})$, it forces $(\mathbf{v}^* - \hat{\mathbf{v}})^T \mathbf{H} (\mathbf{v}^* - \hat{\mathbf{v}}) + (\mathbf{b}^* - \hat{\mathbf{b}})^T (\mathbf{b}^* - \hat{\mathbf{b}}) = 0$, which implies $(\mathbf{v}^* - \hat{\mathbf{v}})^T \mathbf{H} (\mathbf{v}^* - \hat{\mathbf{v}}) = 0$ due to the positive definiteness of \mathbf{H} and $(\mathbf{b}^* - \hat{\mathbf{b}})^T (\mathbf{b}^* - \hat{\mathbf{b}}) = 0$.

In conclusion, $\mathbf{v}^* = \hat{\mathbf{v}}$ and $\mathbf{b}^* = \hat{\mathbf{b}}$. □