## Appendix E: The proof of Theorem 1

Proof. Let us consider Problem (6) directly, rewrite it as following

$$
\begin{align*}
\min _{\mathbf{W}, b, \boldsymbol{\zeta}} & \frac{1}{2} \operatorname{tr}\left(\mathbf{W}^{T} \mathbf{W}\right)+C \sum_{i=1}^{n} \zeta_{i}+\tau\|\mathbf{W}\|_{*}  \tag{19}\\
\text { s.t. } & y_{i}\left[\operatorname{tr}\left(\mathbf{W}^{T} \mathbf{X}_{i}\right)+b\right] \geq 1-\zeta_{i}, \quad i=1, \ldots, n \\
& \zeta_{i} \geq 0, \quad i=1, \ldots, n .
\end{align*}
$$

We construct the following Lagrangian function for (19)

$$
\begin{align*}
& Q(\mathbf{W}, b, \boldsymbol{\zeta}, \boldsymbol{\beta}, \boldsymbol{\mu})  \tag{20}\\
= & \frac{1}{2} \operatorname{tr}\left(\mathbf{W}^{T} \mathbf{W}\right)+C \sum_{i=1}^{n} \zeta_{i}+\tau\|\mathbf{W}\|_{*} \\
& -\sum_{i=1}^{n} \beta_{i}\left\{y_{i}\left[\operatorname{tr}\left(\mathbf{W}^{T} \mathbf{X}_{i}\right)+b\right]-1+\zeta_{i}\right\}-\sum_{i=1}^{n} \mu_{i} \zeta_{i}
\end{align*}
$$

Letting the first-order derivative of $Q$ with respect to $\zeta_{i}$ be 0 , we have

$$
\begin{equation*}
\mu_{i}=C-\beta_{i}, \quad i=1, \ldots, n \tag{21}
\end{equation*}
$$

Substituting (21) in (20) to eliminate $r_{i}$ and $\xi_{i}$, we obtain

$$
\begin{align*}
Q(\mathbf{W}, \boldsymbol{\alpha})= & \frac{1}{2} \operatorname{tr}\left(\mathbf{W}^{T} \mathbf{W}\right)+\tau\|\mathbf{W}\|_{*} \\
& -\sum_{i=1}^{n} \alpha_{i}\left[y_{i} \operatorname{tr}\left(\mathbf{W}^{T} \mathbf{X}_{i}\right)-1\right] \tag{22}
\end{align*}
$$

Since $\mu_{i} \geq 0, \beta_{i}$ should satisfy the following condition

$$
\begin{equation*}
0 \leq \beta_{i} \leq C \tag{23}
\end{equation*}
$$

By KKT condition (Borwein \& Lewis, 2010), we also have 0 should be in the subgradient of $Q$ when the optimal solution is taken:

$$
\begin{equation*}
\left.\mathbf{0} \in \partial Q(\tilde{\mathbf{W}}, \tilde{\boldsymbol{\beta}})\right|_{\mathbf{W}=\tilde{\mathbf{W}}} \tag{24}
\end{equation*}
$$

Based on Eqn. (1), we have

$$
\tilde{\mathbf{W}}=\mathcal{D}_{\tau}\left(\sum_{i=1}^{n} \tilde{\beta}_{i} y_{i} \mathbf{X}_{i}\right)
$$

where $\tilde{\boldsymbol{\beta}}$ is the corresponding value of Lagrangian multiplier when $\tilde{\mathbf{W}}$ is the optimal solution.

$$
\begin{equation*}
S^{*}=\underset{S}{\operatorname{argmax}} E(S) \tag{25}
\end{equation*}
$$

## References

Borwein, Jonathan M and Lewis, Adrian S. Convex analysis and nonlinear optimization: theory and examples, volume 3. Springer Science \& Business Media, 2010.

