

# Supplemental Materials of “Reinforced Angle-based Multicategory Support Vector Machines”

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## Appendix

**Proof of Theorem 1.** To prove Theorem 1, we need the following lemma from Zhang and Liu (2014).

**Lemma 1** (Zhang and Liu, 2014, Lemma 1). *Suppose we have an arbitrary  $\mathbf{f} \in \mathbb{R}^{k-1}$ . For any  $u, v \in \{1, \dots, k\}$  such that  $u \neq v$ , define  $\mathbf{T}_{u,v} = \mathbf{W}_u - \mathbf{W}_v$ . For any scalar  $z \in \mathbb{R}$ ,  $\langle (\mathbf{f} + z\mathbf{T}_{u,v}), \mathbf{W}_w \rangle = \langle \mathbf{f}, \mathbf{W}_w \rangle$ , where  $w \in \{1, \dots, k\}$  and  $w \neq u, v$ . Furthermore, we have that  $\langle (\mathbf{f} + z\mathbf{T}_{u,v}), \mathbf{W}_u \rangle - \langle \mathbf{f}, \mathbf{W}_u \rangle = -\langle (\mathbf{f} + z\mathbf{T}_{v,u}), \mathbf{W}_v \rangle + \langle \mathbf{f}, \mathbf{W}_v \rangle$ .*

The proof consists of two parts. First we show that with  $\gamma \leq 1/2$  the RAMSVM is Fisher consistent. Then we show that when  $\gamma > 1/2$  the Fisher consistency cannot be guaranteed.

In this proof we assume  $P_1 > P_2 \geq \dots \geq P_k$ . We need to show that  $\langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_1 \rangle > \langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_j \rangle$  for  $j \neq 1$ . First, we show that  $\langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_1 \rangle \geq \langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_j \rangle$  for any  $j$ . Note that if this is not true, then by Lemma 1, there exists  $\mathbf{f}'(\mathbf{x}) \in \mathbb{R}^{k-1}$  such that  $\langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_1 \rangle = \langle \mathbf{f}'(\mathbf{x}), \mathbf{W}_j \rangle$  and  $\langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_j \rangle = \langle \mathbf{f}'(\mathbf{x}), \mathbf{W}_1 \rangle$ . One can verify that  $E[V(\mathbf{f}^*(\mathbf{X}), Y)|\mathbf{X} = \mathbf{x}] > E[V(\mathbf{f}'(\mathbf{X}), Y)|\mathbf{X} = \mathbf{x}]$ , which contradicts to the definition of  $\mathbf{f}^*$ .

Next, we show that  $\langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_1 \rangle \leq k - 1$ . Note that we have  $\sum_{j=1}^k \langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_j \rangle = 0$ . If  $\langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_1 \rangle > k - 1$ , there exists  $q$  such that  $\langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_q \rangle < -1$ . By Lemma 1, there exists  $\mathbf{f}'(\mathbf{x}) \in \mathbb{R}^{k-1}$  such that  $\langle \mathbf{f}'(\mathbf{x}), \mathbf{W}_j \rangle = \langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_j \rangle$  for  $j \notin \{1, q\}$ ,  $\langle \mathbf{f}'(\mathbf{x}), \mathbf{W}_1 \rangle = \langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_1 \rangle - \epsilon$ , and  $\langle \mathbf{f}'(\mathbf{x}), \mathbf{W}_q \rangle = \langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_q \rangle + \epsilon$ , where  $\epsilon$  is a small positive number. Now we have  $E[V(\mathbf{f}^*(\mathbf{X}), Y)|\mathbf{X} = \mathbf{x}] - E[V(\mathbf{f}'(\mathbf{X}), Y)|\mathbf{X} = \mathbf{x}] = \{(1 - P_1)(1 - \gamma) + P_k\gamma\}\epsilon > 0$ , which is a contradiction.

Next, we show that if  $\gamma \leq 1/2$ , then  $\langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_j \rangle \geq -1$  for any  $j$ . Suppose this is not true and  $\langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_j \rangle < -1$  for a fixed  $j \neq 1$ . Because the dot product  $\langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_1 \rangle \leq k - 1$  is the maximum among all such dot products, we have that  $-1 < \langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_q \rangle \leq k - 1$  for some  $q$ . Define  $\mathbf{f}'(\mathbf{x})$  such that  $\langle \mathbf{f}'(\mathbf{x}), \mathbf{W}_i \rangle = \langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_i \rangle$  for  $i \notin \{j, q\}$ ,  $\langle \mathbf{f}'(\mathbf{x}), \mathbf{W}_q \rangle = \langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_q \rangle - \epsilon$ , and  $\langle \mathbf{f}'(\mathbf{x}), \mathbf{W}_j \rangle = \langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_j \rangle + \epsilon$ . One can verify that  $E[V(\mathbf{f}'(\mathbf{X}), Y)|\mathbf{X} = \mathbf{x}] - E[V(\mathbf{f}^*(\mathbf{X}), Y)|\mathbf{X} = \mathbf{x}] = \{P_q - 1 + (1 - P_j)\gamma\}\epsilon$ . As  $\gamma \leq 1/2$ ,  $\{P_q - 1 + (1 - P_j)\gamma\} < 0$ , hence this is a contradiction. Therefore, we have  $\langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_j \rangle \geq -1$ .

Lastly, using the above results and an argument similar to Lemma A.2 in Liu and Yuan (2011), we have that  $\langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_1 \rangle = k - 1$  and  $\langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_j \rangle = -1$  for  $j \neq 1$ . This completes the first part of the proof.

For the second part, we show that if  $\gamma > 1/2$ , then the RAMSVM can be inconsistent. We do so by giving a counter example. Let  $k = 3$  and  $P_3 = 0$ . Then  $E[V(\mathbf{f}'(\mathbf{X}), Y)|\mathbf{X} = \mathbf{x}] = \gamma P_1 \{2 - \langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_1 \rangle\}_+ + P_2(1 - \gamma) \{1 + \langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_1 \rangle\}_+ + \gamma P_2 \{2 - \langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_2 \rangle\}_+ + P_1(1 - \gamma) \{1 + \langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_2 \rangle\}_+ + (1 - \gamma) \{1 + \langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_3 \rangle\}_+$ . If  $1/2 < P_1 < \gamma$ , then one can verify that the minimizer  $\mathbf{f}^*$  is such that  $\langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_1 \rangle = \langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_2 \rangle = 2$  and  $\langle \mathbf{f}^*(\mathbf{x}), \mathbf{W}_3 \rangle = -4$ . Therefore, it is not Fisher consistent.  $\square$

Next, we provide the dual problems of Guermeur (2012) and Liu and Yuan (2011). The MSVM framework proposed in Guermeur (2012) used  $K_1$ ,  $K_2$ ,  $K_3$  and  $p$  as hyperparameters to denote different MSVM methods. The values of the hyperparameters that correspond to MSVMs 2-4 and 6 are reported in Table A1.

**Dual Problems of Soft Margin MSVM in Guermeur (2012).** The dual problem of soft margin MSVM in Guermeur (2012) is

$$\begin{aligned}
& \max -\frac{1}{4} \{ \boldsymbol{\alpha}^T M_1 \boldsymbol{\alpha} \} + M_2 \boldsymbol{\alpha}, \\
& s.t. \begin{cases} 0 \leq (1 - K_3)(2 - p)\alpha_{i,j} \leq (2 - p)m(i, j), & i = 1, \dots, n, j \neq y_i, \\ 0 \leq K_3(2 - p) \sum_{j \neq y_i} \alpha_{i,j} \leq (2 - p) \sum_{j \neq y_i} m(i, j), & i = 1, \dots, n, \\ (p - 1)\alpha_{i,j} \geq 0, & i = 1, \dots, n, j \neq y_i, \\ \sum_{i=1}^n \sum_{l=1}^k \{ K_1 \delta_{y_i,j} + (1 - K_1)/k - \delta_{j,l} \} \alpha_{i,l} = 0, & j = 1, \dots, k - 1. \end{cases} \quad (\text{A.1})
\end{aligned}$$

Here  $M_1$  and  $M_2$  are fixed matrices,  $m(i, j)$  is a real number, and  $\delta$  is the Kronecker symbol. Both  $M_1$  and  $M_2$  depend only on the MSVM method, and  $m(i, j)$  depends on  $i, j$  and the MSVM method. For more details about  $M_1, M_2$  and  $m(i, j)$ , see Guermeur (2012). One can verify that for any set of hyperparameters, the equality constraints in (A.1) do not vanish. Notice that (A.1) includes the dual problems of (2) as a special case.

**Dual Problems of Hard Margin MSVM in Guermeur (2012).** The dual problems of hard margin MSVM in Guermeur (2012) can be written as

$$\begin{aligned}
& \max -\frac{1}{4} \{ \boldsymbol{\alpha}^T M'_1 \boldsymbol{\alpha} \} + M'_2 \boldsymbol{\alpha}, \\
& s.t. \begin{cases} \alpha_{i,j} \geq 0, & i = 1, \dots, n, j \neq y_i, \\ \sum_{i=1}^n \sum_{l=1}^k \{ K_1 \delta_{y_i,j} + (1 - K_1)/k - \delta_{j,l} \} \alpha_{i,l} = 0, & j = 1, \dots, k - 1. \end{cases} \quad (\text{A.2})
\end{aligned}$$

Here  $M'_1$  and  $M'_2$  are fixed matrices, similar to  $M_1$  and  $M_2$  in the soft margin case.

| MSVM  | $p$ | $K_1$ | $K_2$   | $K_3$ |
|-------|-----|-------|---------|-------|
| MSVM2 | 1   | 1     | 1       | 0     |
| MSVM3 | 1   | 1     | 1       | 1     |
| MSVM4 | 1   | 0     | 1/(k-1) | 0     |
| MSVM6 | 2   | 0     | 1/(k-1) | 0     |

Table A1: Hyperparameters for different MSVM methods in Guermeur (2012).

**Dual Problems in Liu and Yuan (2011).** For the optimization in Liu and Yuan (2011), its dual problem can be written as

$$\begin{aligned}
& \min \boldsymbol{\beta}^T H \boldsymbol{\beta} + g^T \boldsymbol{\beta}, \\
& s.t. \begin{cases} 0 \leq \alpha_{i,j} \leq A_{i,j}, & i = 1, \dots, j = 1, \dots, k, \\ E \boldsymbol{\beta} = 0, & j = 1, \dots, k, \end{cases} \quad (\text{A.3})
\end{aligned}$$

where  $\boldsymbol{\beta} = (\boldsymbol{\alpha}_1^T, \dots, \boldsymbol{\alpha}_k^T)^T$ , and  $H, E$  are fixed matrices that depend only on the observed predictors and the kernel function  $K(\cdot, \cdot)$ . For more information about  $H$  and  $E$ , see Section 3 in Liu and Yuan (2011).

## References

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