## Agree to Disagree: Adaptive Ensemble Knowledge Distillation in Gradient Space (Supplementary Materials)

## A Proof of Theorem 1

Note that the primal problem Eq. (9) is

$$\min_{\boldsymbol{d}, v, \xi_m} v + C \cdot \sum_{m=1}^{M} \xi_m + \frac{1}{2} \|\boldsymbol{d}\|^2, \text{ s.t. } \langle \nabla_{\boldsymbol{\theta}} \ell_m^t(\boldsymbol{\theta}^{(\tau)}), \boldsymbol{d} \rangle \le v + \xi_m, \ \xi_m \ge 0, \ \forall m \in [1:M].$$
(17)

Its Lagrange function can be written as

$$\mathcal{L}(\boldsymbol{d}, \boldsymbol{v}, \boldsymbol{\xi}_m, \boldsymbol{\alpha}_m, \boldsymbol{\beta}_m) = \boldsymbol{v} + \boldsymbol{C} \cdot \sum_{m=1}^M \boldsymbol{\xi}_m + \frac{1}{2} \|\boldsymbol{d}\|^2 + \sum_{m=1}^M \boldsymbol{\alpha}_m(\langle \nabla_{\boldsymbol{\theta}} \boldsymbol{\ell}_m^t(\boldsymbol{\theta}^{(\tau)}), \boldsymbol{d} \rangle - \boldsymbol{v} - \boldsymbol{\xi}_m) - \sum_{m=1}^M \boldsymbol{\beta}_m \boldsymbol{\xi}_m,$$
(18)

where  $\alpha_m$  and  $\beta_m$  are Lagrange multipliers. Then we have

$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{d}} = \boldsymbol{d} + \sum_{m=1}^{M} \alpha_m \nabla_{\boldsymbol{\theta}} \ell_m^t(\boldsymbol{\theta}^{(\tau)}) = 0, \quad \rightarrow \quad \boldsymbol{d} = -\sum_{m=1}^{M} \alpha_m \nabla_{\boldsymbol{\theta}} \ell_m^t(\boldsymbol{\theta}^{(\tau)}), \tag{19}$$

$$\frac{\partial \mathcal{L}}{\partial v} = 1 - \sum_{m=1}^{M} \alpha_m = 0, \quad \to \quad \sum_{m=1}^{M} \alpha_m = 1, \tag{20}$$

$$\frac{\partial \mathcal{L}}{\partial \xi_m} = C - \alpha_m - \beta_m = 0, \quad \to \quad \alpha_m + \beta_m = C.$$
(21)

The dual problem is thus

$$\min_{\boldsymbol{\alpha}} \left\| \sum_{m=1}^{M} \alpha_m \nabla_{\boldsymbol{\theta}} \ell_m^t(\boldsymbol{\theta}^{(\tau)}) \right\|^2, \text{ s.t. } \sum_{m=1}^{M} \alpha_m = 1, \ 0 \le \alpha_m \le C, \ \forall m \in [1:M].$$
(22)

Denote the optimal solution of Eq. (9) and Eq. (10) as  $(d^*, v^*, \xi_m^*)$  and  $(\alpha_m^*, \beta_m^*)$ , respectively. According to KKT condition, we have

$$\alpha_m^*(\langle \nabla_{\theta} \ell_m^t(\theta^{(\tau)}), d^* \rangle - v^* - \xi_m^*) = 0, \quad \beta_m^* \xi_m^* = 0, \quad \alpha_m^* \xi_m^* = C \xi_m^*.$$
(23)

In this way,

- if d<sup>\*</sup> = 0, then we have ⟨∇<sub>θ</sub>ℓ<sup>t</sup><sub>m</sub>(θ<sup>(τ)</sup>), d<sup>\*</sup>⟩ = 0, which is a trivial case and corresponds to the Pareto critical point.
- if  $d^* \neq 0$ , we have

$$-\|\boldsymbol{d}\|^{2} - v^{*} - C \sum_{m=1}^{M} \xi_{m}^{*} = 0, \qquad (24)$$

which implies that

$$\langle \nabla_{\boldsymbol{\theta}} \ell_m^t(\boldsymbol{\theta}^{(\tau)}), \boldsymbol{d}^* \rangle \le v^* + \xi_m^* = - \|\boldsymbol{d}\|^2 + \xi_m^* - C \sum_{m=1}^M \xi_m^*.$$
 (25)

Then the proof is completed.

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