

## Appendix: Scaling Multi-Instance Support Vector Machine to Breast Cancer Detection on the BreakHis Dataset

### S1 Derivation Details

In this section, we provide the derivation of solution for each variable discussed in Section 3.3. For each variable  $\mathbf{X}$ , we formulate the variable specific objective by keeping the terms containing  $\mathbf{X}$  in Eq. (4). Then we take the derivative of the objective respect to each  $x_i^j \in \mathbf{X}$  and set it to zero matrix to earn the update for  $\mathbf{X}$ .

**E update.** Dropping terms from Eq. (4), that do not contain  $\mathbf{E}$  and decoupling element-wise gives  $K \times N$  problems

$$e_i^m = \arg \min_{e_i^m} C (y_i^m e_i^m)_+ + \frac{\mu}{2} (e_i^m - n_i^m)^2, \quad (\text{S1})$$

where  $n_i^m = y_i^m - q_i^m + r_i^m - \frac{\lambda_i^m}{\mu}$ . Equation (S1) can be differentiated with respect to  $e_i^m$  via the sub-gradient method, and solved in three cases

$$e_i^m = \begin{cases} n_i^m - \frac{C}{\mu} y_i^m & \text{when } y_i^m n_i^m > \frac{C}{\mu}, \\ 0 & \text{when } 0 \leq y_i^m n_i^m \leq \frac{C}{\mu}, \\ n_i^m & \text{when } y_i^m n_i^m < 0, \end{cases} \quad (\text{S2})$$

**Q & R update.** Keeping only terms with  $\mathbf{Q}$  in Eq. (4) and decoupling element-wise gives  $K \times N$  problems

$$q_i^m = \arg \min_{q_i^m} (e_i^m - y_i^m + q_i^m - r_i^m + \lambda_i^m / \mu)^2 + (q_i^m - \max(\mathbf{t}_i^m) + \sigma_i^m / \mu)^2. \quad (\text{S3})$$

Taking the derivative of Eq. (S3) with respect to  $q_i^m$ , setting the result equal to zero, and solving for  $q_i^m$  gives the update

$$q_i^m = \frac{(y_i^m - e_i^m + r_i^m - \lambda_i^m / \mu + \max(\mathbf{t}_i^m) - \sigma_i^m / \mu)}{2}. \quad (\text{S4})$$

Following the same steps for each  $r_i^m \in \mathbf{R}$  we derive the element-wise updates

$$r_i^m = \frac{(e_i^m - y_i^m + q_i^m + \lambda_i^m / \mu + \max(\mathbf{u}_i^m) - \omega_i^m / \mu)}{2}. \quad (\text{S5})$$

**T & U update.** Keeping terms in Eq. (4) containing  $\mathbf{T}$  and decoupling across  $K$  and  $N$  gives the following

$$\mathbf{t}_i^m = \arg \min_{\mathbf{t}_i^m} (q_i^m - \max(\mathbf{t}_i^m) + \sigma_i^m / \mu)^2 + \|\mathbf{t}_i^m - (\mathbf{w}_m^T \mathbf{X}_i + \mathbf{1}b_m) + \theta_i^m / \mu\|_2^2, \quad (\text{S6})$$

which can be further decoupled element-wise for each  $t_{i,j}^m \in \mathbf{t}_i^m$  giving  $K \times N \times (n_1 + \dots + n_N)$  problems

$$t_{i,j}^m = \arg \min_{t_{i,j}^m} \begin{cases} (q_i^m - t_{i,j}^m + \sigma_i^m / \mu)^2 + (t_{i,j}^m - \phi_{i,j}^m)^2 \\ \text{when } t_{i,j}^m = \max(\mathbf{t}_i^m), \\ (t_{i,j}^m - \phi_{i,j}^m)^2 \text{ else,} \end{cases} \quad (\text{S7})$$

where  $\phi_i^m = \mathbf{w}_m^T \mathbf{X}_i + \mathbf{1}b_m - \theta_i^m / \mu$ . Taking the derivative of Eq. (S7) with respect to  $t_{i,j}^m$ , setting the result equal to zero, and solving for  $t_{i,j}^m$ , gives the updates

$$t_{i,j}^m = \begin{cases} \frac{\max(\phi_i^m) + q_i^m + \sigma_i^m / \mu}{2} & \text{if } j = \arg \max(\phi_i^m), \\ \phi_{i,j}^m & \text{else,} \end{cases} \quad (\text{S8})$$

This same strategy is applied to derive the element-wise updates of  $\mathbf{U}$ , giving

$$u_{i,j}^m = \begin{cases} \frac{\max(\psi_i^m) + r_i^m + \omega_i^m / \mu}{2} & \text{if } j = \arg \max(\psi_i^m), \\ \psi_{i,j}^m & \text{else,} \end{cases} \quad (\text{S9})$$

where  $\psi_i^m = \mathbf{w}_y^T \mathbf{X}_i + \mathbf{1}b_y - \xi_i^m / \mu$ . The associated dual variable updates are provided in Algorithm 1.