

Supplementary Material for Budgeted Semi-supervised Support Vector Machine

The general update rule is

$$\begin{aligned}\mathbf{w}_{t+1} &= \mathbf{w}_t - \eta_t g_t - Z_t^l \delta_{l_t} D(x_{l_t}) - Z_t^u \delta_{u_t} D(x_{u_t}) \\ &= \frac{t-1}{t} \mathbf{w}_t + \frac{C \alpha_t y_{i_t}}{t} \Phi(x_{i_t}) + C' \frac{\mu_{u_t v_t}}{t} \beta_t (\Phi(x_{u_t}) - \Phi(x_{v_t})) - Z_t^l \delta_{l_t} D(x_{l_t}) - Z_t^u \delta_{u_t} D(x_{u_t})\end{aligned}$$

We do the convergence analysis for BS3VM with the removal strategy. In this case, the difference vector is $D(x) = \Phi(x)$.

Lemma 1. *Let us denote $s_t = \sum_{i \in I_t^l} |\delta_i| + \sum_{i \in I_t^u} |\delta_i|$. The following statement holds*

$$s_T \leq C + 2C', \forall T$$

Proof. According to the update rule, we have

$$\begin{aligned}s_{t+1} &\leq \frac{t-1}{t} s_t + \frac{C |\alpha_t y_{i_t}|}{t} + \frac{2C' \mu_{u_t v_t} |\beta_t|}{t} \\ &\leq \frac{t-1}{t} s_t + \frac{C + 2C'}{t}\end{aligned}$$

where $\alpha_t = -l'_o(\mathbf{w}_t; x_{i_t}, y_{i_t}) = \mathbb{I}_{y_{i_t} \mathbf{w}_t^\top \Phi(x_{i_t}) \leq 1}$, and $\beta_t = -\text{sign}(\mathbf{w}_t^\top \Phi_{u_t v_t})$.

Here we note that we have used the inequality $\mu_{u_t v_t} = e^{-\frac{\|x_{u_t} - x_{v_t}\|^2}{2\sigma^2}} < 1$. It follows that

$$t s_{t+1} \leq (t-1) s_t + C + 2C'$$

Taking sum when $t = 1, \dots, T-1$, we gain

$$\begin{aligned}(T-1) s_T &\leq (T-1) (C + 2C') \\ s_T &\leq C + 2C'\end{aligned}$$

□

Lemma 2. *The following statement holds*

$$\|\mathbf{w}_t\| \leq C + 2C', \forall t$$

Proof. We have

$$\mathbf{w}_t = \sum_{i \in I_t^l} \delta_i \Phi(x_i) + \sum_{i \in I_t^u} \delta_i \Phi(x_i)$$

It follows that

$$\|\mathbf{w}_t\| \leq \sum_{i \in I_t^l} |\delta_i| \|\Phi(x_i)\| + \sum_{i \in I_t^u} |\delta_i| \|\Phi(x_i)\| \leq \sum_{i \in I_t^l} |\delta_i| + \sum_{i \in I_t^u} |\delta_i| = s_t \leq C + 2C'$$

□

Lemma 3. *The following statement holds*

$$\|g_t\| \leq G = 2(C + 2C'), \forall t$$

Proof. We have

$$g_t = \mathcal{J}'_t(\mathbf{w}_t) = \mathbf{w}_t - C\alpha_t y_{i_t} \Phi(x_{i_t}) - C' \mu_{u_t v_t} \beta_t (\Phi(x_{u_t}) - \Phi(x_{v_t}))$$

where $\alpha_t = -l'_o(\mathbf{w}_t; x_{i_t}, y_{i_t}) = -\mathbb{I}_{y_{i_t} \mathbf{w}_t^\top \Phi(x_{i_t}) \leq 1}$, and $\beta_t = -\text{sign}(\mathbf{w}_t^\top \Phi_{u_t v_t})$.

It follows that

$$\|g_t\| \leq \|\mathbf{w}_t\| + C|\alpha_t| \|\Phi(x_{i_t})\| + C' |\mu_{u_t v_t} \beta_t| \|\Phi(x_{u_t}) - \Phi(x_{v_t})\| \leq 2(C + 2C')$$

□

Lemma 4. *Given two positive integer numbers m, n , assume that before removed the coefficient of $\Phi(x_{l_t})$ is updated m times via the vertex sampling and n times via the edge sampling of the spectral graph. We then have*

$$|\delta_{l_t}| \leq \frac{mC + nC'}{t}$$

Proof. We assume that the coefficient of $\Phi(x_{l_t})$ is updated via the vertex sampling at iterations k_1, \dots, k_m . At the iteration k_j , this coefficient is added by the quantity

$$\frac{-Cl'_o(\mathbf{w}_{k_j}; x_{i_{k_j}}, y_{i_{k_j}})}{k_j}$$

At the iteration t , the above quantity becomes

$$\frac{t-1}{t} \times \frac{t-2}{t-1} \times \dots \times \frac{k_j}{k_j+1} \times \frac{-Cl'_o(\mathbf{w}_{k_j}; x_{i_{k_j}}, y_{i_{k_j}})}{k_j} = \frac{-Cl'_o(\mathbf{w}_{k_j}; x_{i_{k_j}}, y_{i_{k_j}})}{t}$$

We further assume that the coefficient of $\Phi(x_{l_t})$ is updated via the vertex sampling at iterations h_1, \dots, h_n . At the iteration h_j , this coefficient is added by the quantity

$$\frac{-C' \mu_{u_{h_j} v_{h_j}} \text{sign}(\mathbf{w}_{h_j}^\top \Phi_{u_{h_j} v_{h_j}})}{h_j}$$

At the iteration t , the above quantity becomes

$$\frac{t-1}{t} \times \frac{t-2}{t-1} \times \dots \times \frac{h_j}{h_j+1} \times \frac{-C' \mu_{u_{h_j} v_{h_j}} \text{sign}(\mathbf{w}_{h_j}^\top \Phi_{u_{h_j} v_{h_j}})}{h_j} = \frac{-C' \mu_{u_{h_j} v_{h_j}} \text{sign}(\mathbf{w}_{h_j}^\top \Phi_{u_{h_j} v_{h_j}})}{t}$$

Therefore, we have the following representation

$$\delta_{l_t} = \frac{-\sum_{j=1}^m Cl'_o(\mathbf{w}_{k_j}; x_{i_{k_j}}, y_{i_{k_j}}) - \sum_{j=1}^n C' \mu_{u_{h_j} v_{h_j}} \text{sign}(\mathbf{w}_{h_j}^\top \Phi_{u_{h_j} v_{h_j}})}{t}$$

Hence, we gain the conclusion since

$$|\delta_{l_t}| \leq \frac{\sum_{j=1}^m |Cl'_o(\mathbf{w}_{k_j}; x_{i_{k_j}}, y_{i_{k_j}})| + \sum_{j=1}^n |C' \mu_{u_{h_j} v_{h_j}} \text{sign}(\mathbf{w}_{h_j}^\top \Phi_{u_{h_j} v_{h_j}})|}{t} \leq \frac{mC + nC'}{t}$$

□

Lemma 5. *Given a positive integer number p , assume that before removed the coefficient of $\Phi(x_{u_t})$ is updated p times via edge sampling. We then have*

$$|\delta_{u_t}| \leq \frac{pC'}{t}$$

Proof. We skip this proof since it is similar to that of Lemma 4. □

Lemma 6. *We define $\rho_i = \frac{\delta_i}{\eta_t} = t\delta_i$ and $h_t = Z_t^l \rho_{l_t} D(x_{l_t}) + Z_t^u \rho_{u_t} D(x_{u_t})$. Then we have*

$$\|h_t\| \leq H = mC + (n+p)C', \forall t$$

Proof. We have

$$\|h_t\| \leq |\rho_{l_t}| \|D(x_{l_t})\| + |\rho_{u_t}| \|D(x_{u_t})\| \leq |\rho_{l_t}| \|\Phi(x_{l_t})\| + |\rho_{u_t}| \|\Phi(x_{u_t})\| \leq mC + (n+p)C' = H$$

□

Lemma 7. *The following statement holds*

$$\mathbb{E} \left[\|\mathbf{w}_t - \mathbf{w}^*\|^2 \right]^{1/2} \leq W, \forall t$$

where $W = H + \sqrt{H^2 + (G+H)^2}$.

Proof. We have

$$\begin{aligned} \|\mathbf{w}_{t+1} - \mathbf{w}^*\|^2 &= \|\mathbf{w}_t - \eta_t g_t - Z_t^l \delta_{l_t} D(x_{l_t}) - Z_t^u \delta_{u_t} D(x_{u_t}) - \mathbf{w}^*\|^2 \\ &= \|\mathbf{w}_t - \eta_t g_t - \eta_t h_t - \mathbf{w}^*\|^2 = \|\mathbf{w}_t - \mathbf{w}^*\|^2 + \eta_t^2 \|g_t + h_t\|^2 - 2\eta_t (\mathbf{w}_t - \mathbf{w}^*)^\top g_t - 2\eta_t (\mathbf{w}_t - \mathbf{w}^*)^\top h_t \end{aligned}$$

Taking the conditional expectation w.r.t \mathbf{w}_t , we gain

$$\begin{aligned} \mathbb{E} \left[\|\mathbf{w}_{t+1} - \mathbf{w}^*\|^2 \right] &\leq \mathbb{E} \left[\|\mathbf{w}_t - \mathbf{w}^*\|^2 \right] + \eta_t^2 (G+H)^2 - 2\eta_t (\mathbf{w}_t - \mathbf{w}^*)^\top \mathbb{E}[g_t] - 2\eta_t (\mathbf{w}_t - \mathbf{w}^*)^\top \mathbb{E}[h_t] \\ &\leq \mathbb{E} \left[\|\mathbf{w}_t - \mathbf{w}^*\|^2 \right] + \eta_t^2 (G+H)^2 - 2\eta_t (\mathbf{w}_t - \mathbf{w}^*)^\top \mathcal{J}'(\mathbf{w}_t) - 2\eta_t (\mathbf{w}_t - \mathbf{w}^*)^\top \mathbb{E}[h_t] \\ &\leq \mathbb{E} \left[\|\mathbf{w}_t - \mathbf{w}^*\|^2 \right] + \eta_t^2 (G+H)^2 - \frac{2\eta_t \|\mathbf{w}_t - \mathbf{w}^*\|^2}{2} - 2\eta_t (\mathbf{w}_t - \mathbf{w}^*)^\top \mathbb{E}[h_t] \end{aligned}$$

Here we note that we have used the following inequality

$$(\mathbf{w}_t - \mathbf{w}^*)^\top \mathcal{J}'(\mathbf{w}_t) \geq \mathcal{J}(\mathbf{w}_t) - \mathcal{J}(\mathbf{w}^*) + \frac{1}{2} \|\mathbf{w}_t - \mathbf{w}^*\|^2 \geq \frac{1}{2} \|\mathbf{w}_t - \mathbf{w}^*\|^2$$

Taking the expectation again, we achieve

$$\begin{aligned} \mathbb{E} \left[\|\mathbf{w}_{t+1} - \mathbf{w}^*\|^2 \right] &\leq \frac{t-1}{t} \mathbb{E} \left[\|\mathbf{w}_t - \mathbf{w}^*\|^2 \right] + \eta_t^2 (G+H)^2 - 2\eta_t \mathbb{E} \left[(\mathbf{w}_t - \mathbf{w}^*)^\top h_t \right] \\ &\leq \frac{t-1}{t} \mathbb{E} \left[\|\mathbf{w}_t - \mathbf{w}^*\|^2 \right] + \eta_t^2 (G+H)^2 + 2\eta_t \mathbb{E} \left[\|\mathbf{w}_t - \mathbf{w}^*\|^2 \right]^{1/2} \mathbb{E} \left[\|h_t\|^2 \right]^{1/2} \\ &\leq \frac{t-1}{t} \mathbb{E} \left[\|\mathbf{w}_t - \mathbf{w}^*\|^2 \right] + \frac{(G+H)^2}{t} + \frac{2H \mathbb{E} \left[\|\mathbf{w}_t - \mathbf{w}^*\|^2 \right]^{1/2}}{t} \end{aligned}$$

Choosing $W = H + \sqrt{H^2 + (G+H)^2}$, we have the following: if $\mathbb{E} \left[\|\mathbf{w}_t - \mathbf{w}^*\|^2 \right] \leq W^2$, $\mathbb{E} \left[\|\mathbf{w}_{t+1} - \mathbf{w}^*\|^2 \right] \leq W^2$. □

Theorem 8. *Let us consider the running of Algorithm 1. The following statement holds*

$$\begin{aligned} \mathbb{E} [\mathcal{J}(\bar{\mathbf{w}}_t)] - \mathcal{J}(\mathbf{w}^*) &\leq \frac{1}{T} \sum_{t=1}^T \mathbb{E} [\mathcal{J}(\mathbf{w}_t)] - \mathcal{J}(\mathbf{w}^*) \\ &\leq \frac{(G+H)^2 (\log T + 1)}{2T} + \frac{W}{T} \sum_{t=1}^T \mathbb{P}(Z_t^l = 1) \mathbb{E} [\rho_{l_t}^2]^{1/2} \\ &\quad + \frac{W}{T} \sum_{t=1}^T \mathbb{P}(Z_t^u = 1) \mathbb{E} [\rho_{u_t}^2]^{1/2} \end{aligned}$$

where $\rho_{l_t} = \frac{\delta_{l_t}}{\eta_t}$ and $\rho_{u_t} = \frac{\delta_{u_t}}{\eta_t}$.

Proof. We have

$$\begin{aligned} \|\mathbf{w}_{t+1} - \mathbf{w}^*\|^2 &= \|\mathbf{w}_t - \eta_t g_t - Z_t^l \delta_{l_t} D(x_{l_t}) - Z_t^u \delta_{u_t} D(x_{u_t}) - \mathbf{w}^*\|^2 \\ &= \|\mathbf{w}_t - \eta_t g_t - \eta_t h_t - \mathbf{w}^*\|^2 = \|\mathbf{w}_t - \mathbf{w}^*\|^2 + \eta_t^2 \|g_t + h_t\|^2 - 2\eta_t (\mathbf{w}_t - \mathbf{w}^*)^\top g_t - 2\eta_t (\mathbf{w}_t - \mathbf{w}^*)^\top h_t \end{aligned}$$

$$\begin{aligned}
(\mathbf{w}_t - \mathbf{w}^*)^\top g_t &= \frac{\|\mathbf{w}_t - \mathbf{w}^*\|^2 - \|\mathbf{w}_{t+1} - \mathbf{w}^*\|^2}{2\eta_t} + \frac{\eta_t \|g_t + h_t\|^2}{2} - (\mathbf{w}_t - \mathbf{w}^*)^\top h_t \\
&= \frac{\|\mathbf{w}_t - \mathbf{w}^*\|^2 - \|\mathbf{w}_{t+1} - \mathbf{w}^*\|^2}{2\eta_t} + \frac{\eta_t \|g_t + h_t\|^2}{2} - (\mathbf{w}_t - \mathbf{w}^*)^\top (Z_t^l \rho_{l_t} \Phi(x_{l_t}) + Z_t^u \rho_{u_t} \Phi(x_{u_t}))
\end{aligned}$$

Taking the conditional expectation w.r.t $\mathbf{w}_1, \dots, \mathbf{w}_t, x_1, \dots, x_t$ of two sides on the above inequality, we gain

$$\begin{aligned}
(\mathbf{w}_t - \mathbf{w}^*)^\top \mathcal{J}'(\mathbf{w}_t) &\leq \frac{\mathbb{E}[\|\mathbf{w}_t - \mathbf{w}^*\|^2] - \mathbb{E}[\|\mathbf{w}_{t+1} - \mathbf{w}^*\|^2]}{2\eta_t} + \frac{\eta_t (G + H)^2}{2} \\
&\quad - (\mathbf{w}_t - \mathbf{w}^*)^\top (\mathbb{E}[Z_t^l] \rho_{l_t} \Phi(x_{l_t}) + \mathbb{E}[Z_t^u] \rho_{u_t} \Phi(x_{u_t})) \\
\mathcal{J}(\mathbf{w}_t) - \mathcal{J}(\mathbf{w}^*) + \frac{1}{2} \|\mathbf{w}_t - \mathbf{w}^*\|^2 &\leq \frac{\mathbb{E}[\|\mathbf{w}_t - \mathbf{w}^*\|^2] - \mathbb{E}[\|\mathbf{w}_{t+1} - \mathbf{w}^*\|^2]}{2\eta_t} + \frac{\eta_t (G + H)^2}{2} \\
&\quad - (\mathbf{w}_t - \mathbf{w}^*)^\top (\mathbb{P}(Z_t^l = 1) \rho_{l_t} \Phi(x_{l_t}) + \mathbb{P}(Z_t^u = 1) \rho_{u_t} \Phi(x_{u_t}))
\end{aligned}$$

Here we note that ρ_{l_t} and ρ_{u_t} are functionally dependent on $\mathbf{w}_1, \dots, \mathbf{w}_t, x_1, \dots, x_t$ and $\mathcal{J}(\mathbf{w})$ is 1-strongly convex function. Taking the expectation of two sides of the above inequality, we obtain

$$\begin{aligned}
\mathbb{E}[\mathcal{J}(\mathbf{w}_t) - \mathcal{J}(\mathbf{w}^*)] &\leq \frac{t-1}{2} \mathbb{E}[\|\mathbf{w}_t - \mathbf{w}^*\|^2] - \frac{t}{2} \mathbb{E}[\|\mathbf{w}_{t+1} - \mathbf{w}^*\|^2] + \frac{(G + H)^2}{2t} \\
&\quad - \mathbb{P}(Z_t^l = 1) \mathbb{E}[(\mathbf{w}_t - \mathbf{w}^*)^\top \rho_{l_t} \Phi(x_{l_t})] - \mathbb{P}(Z_t^u = 1) \mathbb{E}[(\mathbf{w}_t - \mathbf{w}^*)^\top \rho_{u_t} \Phi(x_{u_t})] \\
&\leq \frac{t-1}{2} \mathbb{E}[\|\mathbf{w}_t - \mathbf{w}^*\|^2] - \frac{t}{2} \mathbb{E}[\|\mathbf{w}_{t+1} - \mathbf{w}^*\|^2] + \frac{(G + H)^2}{2t} \\
&\quad + \mathbb{P}(Z_t^l = 1) \mathbb{E}[\|\mathbf{w}_t - \mathbf{w}^*\|^2]^{1/2} \mathbb{E}[\|\rho_{l_t} \Phi(x_{l_t})\|^2]^{1/2} \\
&\quad + \mathbb{P}(Z_t^u = 1) \mathbb{E}[\|\mathbf{w}_t - \mathbf{w}^*\|^2]^{1/2} \mathbb{E}[\|\rho_{u_t} \Phi(x_{u_t})\|^2]^{1/2} \\
&\leq \frac{t-1}{2} \mathbb{E}[\|\mathbf{w}_t - \mathbf{w}^*\|^2] - \frac{t}{2} \mathbb{E}[\|\mathbf{w}_{t+1} - \mathbf{w}^*\|^2] + \frac{(G + H)^2}{2t} \\
&\quad + \mathbb{P}(Z_t^l = 1) W \mathbb{E}[\rho_{l_t}^2]^{1/2} + \mathbb{P}(Z_t^u = 1) W \mathbb{E}[\rho_{u_t}^2]^{1/2}
\end{aligned}$$

Taking sum when $t = 1, \dots, T$, we gain

$$\begin{aligned}
\sum_{t=1}^T \mathbb{E}[\mathcal{J}(\mathbf{w}_t) - \mathcal{J}(\mathbf{w}^*)] &\leq \frac{(G + H)^2}{2} \sum_{t=1}^T \frac{1}{t} + W \sum_{t=1}^T \mathbb{P}(Z_t^l = 1) \mathbb{E}[\rho_{l_t}^2]^{1/2} + W \sum_{t=1}^T \mathbb{P}(Z_t^u = 1) \mathbb{E}[\rho_{u_t}^2]^{1/2} \\
\frac{1}{T} \sum_{t=1}^T \mathbb{E}[\mathcal{J}(\mathbf{w}_t) - \mathcal{J}(\mathbf{w}^*)] &\leq \frac{(G + H)^2 (\log T + 1)}{2T} + \frac{W}{T} \sum_{t=1}^T \mathbb{P}(Z_t^l = 1) \mathbb{E}[\rho_{l_t}^2]^{1/2} + \frac{W}{T} \sum_{t=1}^T \mathbb{P}(Z_t^u = 1) \mathbb{E}[\rho_{u_t}^2]^{1/2} \\
\mathbb{E}[\mathcal{J}(\bar{\mathbf{w}}_T) - \mathcal{J}(\mathbf{w}^*)] &\leq \frac{1}{T} \sum_{t=1}^T \mathbb{E}[\mathcal{J}(\mathbf{w}_t) - \mathcal{J}(\mathbf{w}^*)] \leq \frac{(G + H)^2 (\log T + 1)}{2T} + \frac{W}{T} \sum_{t=1}^T \mathbb{P}(Z_t^l = 1) \mathbb{E}[\rho_{l_t}^2]^{1/2} \\
&\quad + \frac{W}{T} \sum_{t=1}^T \mathbb{P}(Z_t^u = 1) \mathbb{E}[\rho_{u_t}^2]^{1/2}
\end{aligned}$$

□