

////////// Bonus Problem //////////

21. We want to show that $y_{n(t)} \mathbf{w}_{t+1}^T \mathbf{x}_{n(t)} > 0$ with the new update rule. So, we substitute the \mathbf{w}_{t+1} with the new one.

$$\begin{aligned}
 y_{n(t)} \mathbf{w}_{t+1}^T \mathbf{x}_{n(t)} &= y_{n(t)} \left\{ \mathbf{w}_t + y_{n(t)} \mathbf{x}_{n(t)} \left[\frac{-y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)}}{\|\mathbf{x}_{n(t)}\|^2} + 1 \right] \right\}^T \mathbf{x}_{n(t)} \\
 &= y_{n(t)} \left\{ \mathbf{w}_t + \left[\overset{=-1}{\frac{-y_{n(t)}^2 \mathbf{w}_t^T \|\mathbf{x}_{n(t)}\|^2}{\|\mathbf{x}_{n(t)}\|^2}} + y_{n(t)} \mathbf{x}_{n(t)} \right] \right\}^T \mathbf{x}_{n(t)} \\
 &= y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)} - \underbrace{\left[y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)} \right]}_{= \|\mathbf{x}_{n(t)}\|^2} + y_{n(t)}^2 \|\mathbf{x}_{n(t)}\|^2 > 0
 \end{aligned}$$

22. We want to prove that the PLA will halt in a perfect line if data is linear separable and using the new update rule.

If data is linear separable, it means there exist a \mathbf{w}_f that every \mathbf{x}_n correctly away from the line.

Hence, we know that $y_{n(t)} \mathbf{w}_f^T \mathbf{x}_{n(t)} \geq \min_n y_n \mathbf{w}_f^T \mathbf{x}_n > 0$. Moreover, the update only occur when mistake; so, $y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)} \leq 0$.

Now, we using the skill taught in class in lecture 2, in page 14-15. We want to prove that each update can make the \mathbf{w}_t more close to the \mathbf{w}_f with the new update rule.

$$\because y_{n(t)} \neq \text{sign}(\mathbf{w}_t^T \mathbf{x}_{n(t)}) \quad \therefore -y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)} > 0 \Rightarrow \left[\frac{-y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)}}{\|\mathbf{x}_{n(t)}\|^2} \right] \geq 0 \Rightarrow \left[\frac{-y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)}}{\|\mathbf{x}_{n(t)}\|^2} + 1 \right] \geq 1$$

First, we want to prove that first equation $\mathbf{w}_f^T \mathbf{w}_{t+1} \geq \mathbf{w}_f^T \mathbf{w}_t$ still hold.

$$\begin{aligned}
 \mathbf{w}_f^T \mathbf{w}_{t+1} &= \mathbf{w}_f^T \left(\mathbf{w}_t + y_{n(t)} \mathbf{x}_{n(t)} \left[\frac{-y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)}}{\|\mathbf{x}_{n(t)}\|^2} + 1 \right] \right) \\
 &\geq \mathbf{w}_f^T (\mathbf{w}_t + y_{n(t)} \mathbf{x}_{n(t)}) \\
 &\geq \mathbf{w}_f^T \mathbf{w}_t + \min_n y_{n(t)} \mathbf{w}_f^T \mathbf{x}_{n(t)} \\
 &\geq \mathbf{w}_f^T \mathbf{w}_t + 0
 \end{aligned}$$

Second, we want to prove that the growth of $\|\mathbf{w}_{t+1}\|^2$ is limited.

$$\begin{aligned}
\|\mathbf{w}_{t+1}\|^2 &= \left\| \mathbf{w}_t + y_{n(t)} \mathbf{x}_{n(t)} \left[\frac{-y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)}}{\|\mathbf{x}_{n(t)}\|^2} + 1 \right] \right\|^2 \\
&= \left\| \mathbf{w}_t \right\|^2 + \underbrace{2y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)}}_{\leq 0} \left[\underbrace{\frac{-y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)}}{\|\mathbf{x}_{n(t)}\|^2} + 1}_{\geq 1} \right] + \left\| y_{n(t)} \mathbf{x}_{n(t)} \left[\frac{-y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)}}{\|\mathbf{x}_{n(t)}\|^2} + 1 \right] \right\|^2 \\
&\leq \left\| \mathbf{w}_t \right\|^2 + 2y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)} + \left\| y_{n(t)} \mathbf{x}_{n(t)} \left[\frac{-y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)}}{\|\mathbf{x}_{n(t)}\|^2} + 1 \right] \right\|^2 \\
&\leq \left\| \mathbf{w}_t \right\|^2 + 2y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)} + \left\| \frac{-y_{n(t)}^2 \mathbf{w}_t^T \mathbf{x}_{n(t)}}{\|\mathbf{x}_{n(t)}\|^2} + y_{n(t)} \mathbf{x}_{n(t)} \right\|^2 \\
&= \left\| \mathbf{w}_t \right\|^2 + 2y_{n(t)} \mathbf{w}_t^T \mathbf{x}_{n(t)} + \left\| -\mathbf{w}_t + y_{n(t)} \mathbf{x}_{n(t)} \right\|^2 \\
&= 2\left\| \mathbf{w}_t \right\|^2 + \left\| \mathbf{x}_{n(t)} \right\|^2 \\
&\leq 2\left\| \mathbf{w}_t \right\|^2 + \max_n \left\| \mathbf{x}_{n(t)} \right\|^2
\end{aligned}$$

From the above result, we can derive that if we start from $\mathbf{w} = 0$, $\frac{\mathbf{w}_f^T \mathbf{w}_t}{\|\mathbf{w}_f\| \|\mathbf{w}_t\|} \geq f(t) \times \text{const.}$

$$\begin{aligned}
\frac{\mathbf{w}_f^T \mathbf{w}_t}{\|\mathbf{w}_f\| \|\mathbf{w}_t\|} &\geq \frac{\mathbf{w}_f^T \times t \times \min_n y_{n(t)} \mathbf{x}_{n(t)}}{\|\mathbf{w}_f\| \|\mathbf{w}_t\|} \\
&= t \times \frac{\min_n y_{n(t)} \mathbf{w}_f^T \mathbf{x}_{n(t)}}{\|\mathbf{w}_f\|} \times \frac{1}{\sqrt{\|\mathbf{w}_t\|^2}} \\
&\geq t \times \frac{\min_n y_{n(t)} \mathbf{w}_f^T \mathbf{x}_{n(t)}}{\|\mathbf{w}_f\|} \times \frac{1}{\sqrt{2\|\mathbf{w}_t\|^2 + \max_n \|\mathbf{x}_{n(t)}\|^2}} \\
&\geq t \times \frac{\min_n y_{n(t)} \mathbf{w}_f^T \mathbf{x}_{n(t)}}{\|\mathbf{w}_f\|} \times \frac{1}{\sqrt{2t \max_n \|\mathbf{x}_{n(t)}\|^2}} \\
&\geq t \times \frac{\min_n y_{n(t)} \mathbf{w}_f^T \mathbf{x}_{n(t)}}{\|\mathbf{w}_f\|} \times \frac{1}{\sqrt{t} \sqrt{2 \max_n \|\mathbf{x}_{n(t)}\|^2}} \\
&= \frac{t}{\sqrt{t}} \times \frac{\min_n y_{n(t)} \mathbf{w}_f^T \mathbf{x}_{n(t)}}{\|\mathbf{w}_f\|} \times \frac{1}{\sqrt{2 \max_n \|\mathbf{x}_{n(t)}\|^2}} \\
&\geq \sqrt{t} \times \text{const.}
\end{aligned}$$

Finally, we conclude that \mathbf{w}_t can close to the \mathbf{w}_f by each update step with new update rule and

maximum value of $\frac{\mathbf{w}_f^T \mathbf{w}_t}{\|\mathbf{w}_f\| \|\mathbf{w}_t\|}$ will be 1.