## DSC 140A - Discussion 04

## Problem 1.

Using the definition, show that the function $f(\vec{w})=a \vec{x} \cdot \vec{w}-b$ is convex as a function of $\vec{w}$, where $a, b \in \mathbb{R}$ and $\vec{x}, \vec{w} \in \mathbb{R}^{d}$.

## Solution:

$$
\begin{aligned}
& \nabla f(\vec{w})=a \vec{x} \\
& H_{f}(\vec{w})=\mathbf{0}_{d, d} \succeq 0
\end{aligned}
$$

In the Hessian, $H_{f}(\vec{w})$, all values are 0 . We can see that the eigenvalues will also be 0 . Therefore, $f(\vec{w})$ is convex.

## Problem 2.

Let $f_{1}(\vec{w})$ and $f_{2}(\vec{w})$ be convex functions from $\mathbb{R}^{d}$ to $\mathbb{R}$. Define

$$
f(\vec{w})=\max \left\{f_{1}(\vec{w}), f_{2}(\vec{w})\right\}
$$

Show that $f(\vec{w})$ is convex.

## Solution:

Take $t \in[0,1]$.

$$
\begin{aligned}
f\left(t \vec{w}_{1}+(1-t) \vec{w}_{2}\right) & =\max \left\{f_{1}\left(t \vec{w}_{1}+(1-t) \vec{w}_{2}\right), f_{2}\left(t \vec{w}_{1}+(1-t) \vec{w}_{2}\right)\right\} \\
& \left.\leq \max \left\{t f_{1}\left(\vec{w}_{1}\right)+(1-t) f_{1}\left(\vec{w}_{2}\right), t f_{2}\left(\vec{w}_{1}\right)+(1-t) f_{2}\left(\vec{w}_{2}\right)\right\} \quad \text { (due to convexity of } f_{1}, f_{2}\right) \\
& \leq \max \left\{t f_{1}\left(\vec{w}_{1}\right), t f_{2}\left(\vec{w}_{1}\right)\right\}+\max \left\{(1-t) f_{1}\left(\vec{w}_{2}\right),(1-t) f_{2}\left(\vec{w}_{2}\right)\right\} \\
& =t \max \left\{f_{1}\left(\vec{w}_{1}\right), f_{2}\left(\vec{w}_{1}\right)\right\}+(1-t) \max \left\{f_{1}\left(\vec{w}_{2}\right), f_{2}\left(\vec{w}_{2}\right)\right\} \\
& =t f\left(w_{1}\right)+(1-t) f\left(w_{2}\right)
\end{aligned}
$$

## Problem 3.

Recall that the Perceptron loss is:

$$
L_{\mathrm{perc}}(\vec{w}, \vec{x}, y)= \begin{cases}0, & \text { if } \operatorname{sign}(\vec{w} \cdot \vec{x})=y \text { (correctly classified) } \\ |\vec{w} \cdot \vec{x}|, & \text { if } \operatorname{sign}(\vec{w} \cdot \vec{x}) \neq y \text { (misclassified) }\end{cases}
$$

Using the trick that $-y \vec{w} \cdot \vec{x}=|\vec{w} \cdot \vec{x}|$ in the case of misclassification, this can be be written in the equivalent form:

$$
L_{\text {perc }}(\vec{w}, \vec{x}, y)=\max \{0,-y \vec{w} \cdot \vec{x}\}
$$

Argue that the perceptron loss is convex as a function of $\vec{w}$.
Solution: We'll argue that the loss is the maximum of two convex functions, which (by Problem 2 above) is convex.

Let $f_{1}(\vec{w})=0$ and $f_{2}(\vec{w})=-y \vec{w} \cdot \vec{x}$. Recognize that

$$
L_{\text {perc }}(\vec{w}, \vec{x}, y)=\max \left\{f_{1}(\vec{w}), f_{2}(\vec{w})\right\}
$$

$f_{2}$ is convex by the result of Problem 1 (with $a=y$ and $b=0$ ). $f_{1}$ is constant, and trivially convex. Therefore $L_{\text {perc }}$ is convex by the result of Problem 2.

