

HW 1

N1

$g(x)$ is convex if

$$f(\lambda x + (1-\lambda)y) \leq \lambda f(x) + (1-\lambda)f(y) \quad \forall x, y \in f$$

$f(x)$ is convex then $g(x) = f(Ax+b)$ is convex.

Proof!

$$\begin{aligned} g(\lambda x + (1-\lambda)y) &= f(A(\lambda x + (1-\lambda)y) + b) \\ &= f(\lambda Ax + (1-\lambda)Ay + b) = \\ &= f(\lambda Ax + b\lambda - b\lambda + (1-\lambda)Ay + b) = \\ &= f(\lambda(Ax+b) + Ay - \lambda Ay + b - b\lambda) = \\ &= f(\lambda(Ax+b) + (1-\lambda)(Ay+b)) \\ &\leq \lambda f(Ax+b) + (1-\lambda)f(Ay+b) \text{ by convexity of } f. \end{aligned}$$



b) $f_1(x), \dots, f_n(x)$ are conv.

$$h = \max\{f_1(x), \dots, f_n(x)\}$$

Proof! $h(\lambda x + (1-\lambda)y) =$

$$\max\{f_1(\lambda x + (1-\lambda)y), \dots, f_n(\lambda x + (1-\lambda)y)\} \leq$$

$$\leq \max\{\lambda f_1(x) + (1-\lambda)f_1(y), \dots, \lambda f_n(x) + (1-\lambda)f_n(y)\}$$

$$\leq \max\{\lambda f_1(x), \dots, \lambda f_n(x)\} + \max\{(1-\lambda)f_1(y), \dots, (1-\lambda)f_n(y)\}$$

$$= \lambda \max\{f_1(x), \dots, f_n(x)\} + (1-\lambda) \max\{f_1(y), \dots, f_n(y)\}$$

$$= \lambda h + (1-\lambda)h \quad \blacksquare$$

c) $\lambda > 0$, $v, u \in \arg \min f(w)$

$f(x)$ is λ -strong convex if

$$\forall x, y \quad f(y) \leq f(x) + \nabla f(x)^T (y-x) + \frac{\lambda}{2} \|y-x\|^2$$

Let $u \neq v$. Then, there will be two points

$$x_1 \neq x_2 \text{ where } \nabla f(x_1) = \nabla f(x_2) = 0 \quad (1)$$

$$\text{Then, } f(x_1) \leq f(x_2) + \nabla f(x_2)^T (x_1 - x_2) + \frac{\lambda}{2} \|x_1 - x_2\|^2$$

which is equivalent to

$$\langle \nabla f(x_1) - \nabla f(x_2), x_1 - x_2 \rangle \geq \lambda \|x_1 - x_2\|^2$$

Since $\nabla f(x_1) - \nabla f(x_2) = 0$, LHS = 0

Also, $\lambda > 0$ and $\|x_1 - x_2\|_2^2 > 0$ by (1)

Therefore, $0 \geq \lambda \|x_1 - x_2\| > 0$

which is a contradiction \blacksquare

d) $\Omega =]0, 1[$ $f(x) = x$ The function is differentiable everywhere except at $\{0, 1\}$.

Then, ∂f becomes $(-\infty, 1], x=0, \{1\}, x \in (0, 1)$

So, as we see, by any means, $0 \in \partial f(x^*)$, where x^* is obviously 0.

$$\frac{1}{p} + \frac{1}{q} = 1 \quad \sqrt{2}. \quad \|z\|_c = \left(\sum |z_i|^c \right)^{\frac{1}{c}}, \quad \begin{matrix} 1 < p < 2 \\ 2 \leq q < \infty \end{matrix}$$

a) $a, b \geq 0$, $ab \leq \frac{a^p}{p} + \frac{b^q}{q}$ concave
 Let $\frac{1}{p} = t$ $\frac{1}{q} = 1-t$ ln is

$$ab \leq a^{\frac{1}{t}} t + b^{(1-t)} (1-t) \quad \text{Let's keep } p \text{ and } q \text{ in expon.}$$

$$\ln a + \ln b \leq \ln(a^p t + (1-t)b^q)$$

$$\geq \ln(a^p) t + (1-t) \ln b = \ln a \frac{1}{p} t + \ln b \frac{1-t}{1-t}$$

$$\ln(a^p) t + (1-t) \ln(b^q) \geq \ln a + \ln b = \ln ab$$

The inequality strictly holds if $a^p = b^q$

$$b) \langle x, y \rangle \leq \frac{\|x\|_p^p}{p} + \frac{\|y\|_p^p}{q} = \frac{\sum_{i=1}^d |x_i|^p}{p} + \frac{\sum_{i=1}^d |y_i|^q}{q}$$

$$= \sum_{i=1}^d \left(\frac{|x_i|^p}{p} + \frac{|y_i|^q}{q} \right) \geq \sum_{i=1}^d x_i y_i \text{ which}$$

holds because of Young's inequality. = from
a) directly

$$c) \langle x, y \rangle \leq \|x\|_p + \|y\|_p$$

Proof: Let's commit substitution,

$$t_i = \frac{x_i}{\left(\sum_{i=1}^d |x_i|^p\right)^{\frac{1}{p}}} \quad z_i = \frac{y_i}{\left(\sum_{i=1}^d |y_i|^q\right)^{\frac{1}{q}}}$$

Now, having b)

$$\sum_{i=1}^d |t_i z_i| \leq \sum_{i=1}^d \left(\frac{|t_i|^p}{p} + \frac{|z_i|^q}{q} \right)$$

$$\text{Then, } \sum_{i=1}^d \left(\frac{|t_i|^p}{p} + \frac{|z_i|^q}{q} \right) = \sum_{i=1}^d \left(\frac{|x_i|^p}{p \left(\sum_{i=1}^d |x_i|^p\right)^{\frac{1}{p}}} + \frac{|y_i|^q}{q \left(\sum_{i=1}^d |y_i|^q\right)^{\frac{1}{q}}} \right) \leq$$

because $\sum_{i=1}^d |t_i|^p = \frac{\sum_{i=1}^d |x_i|^p}{\left(\sum_{i=1}^d |x_i|^p\right)^{\frac{1}{p}} \cdot p} = 1$ Same for z_i .

$$\text{Hence, } \sum \frac{|t_i|^p}{p} + \frac{|z_i|^q}{q} = \frac{1}{p} + \frac{1}{q} = 1, \text{ so } \sum |t_i z_i| \leq 1$$

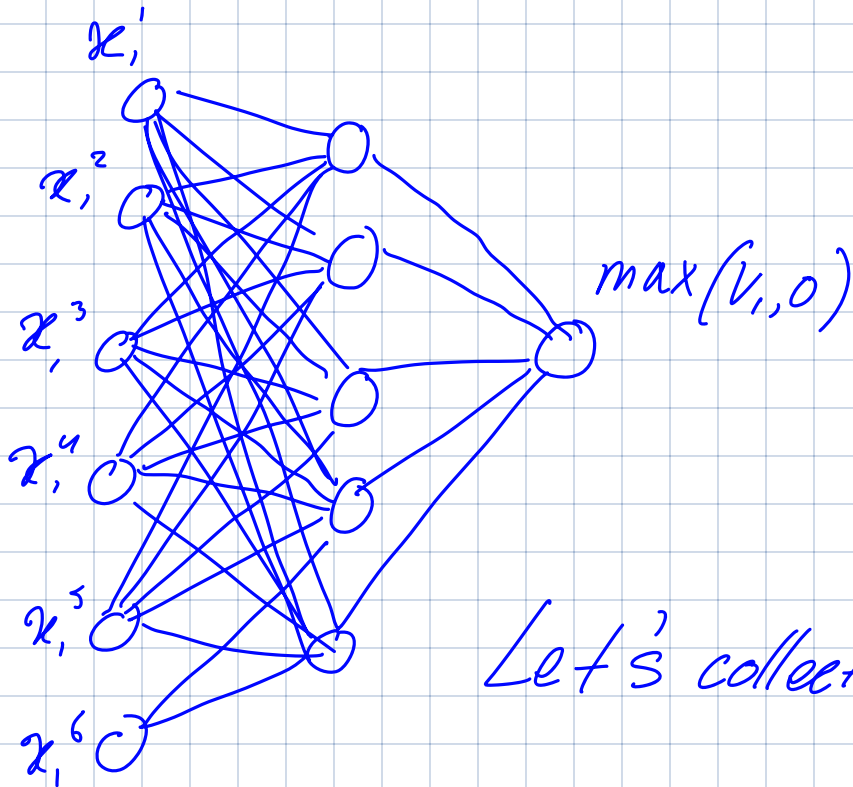
After multiplying by $\left(\sum_{i=1}^d |x_i|^p\right)^{\frac{1}{p}} \left(\sum_{i=1}^d |y_i|^q\right)^{\frac{1}{q}}$ so the proof is done.

✓ 3.

$$\mathcal{F}_n = \{h_{w_1, \dots, w_n} : \forall i, w_i \in \mathbb{R}_+^{N_i \times N_{i-1}}, \forall i \|w_i\|_1 = B, \}$$

$$N_0 = d \quad N_n = 1.$$

Let $n=1$, then $w_1 \in \mathbb{R}_+^{d \times d-1}$



Let's collect some facts:

- 1) First, notice that we can have no more than d layers. Moreover, we can have only $\sum_{i=1}^{d-n} i$ nodes. Therefore, the amount of weights is $\sum_{i=1}^{d-n} i \cdot (i-1)$
- 2) ReLU is a 1-Lipschitz function.

Therefore, by contraction inequality,

$$\text{Rad}(\sigma(Wx)) = \text{Rad}(\sigma(\langle W, x \rangle)) \leq \text{Rad}(\langle W, x \rangle)$$

The Rad of linear predictor of ℓ_1 -norm is $B_{1,\infty} \sqrt{\frac{2 \ln(2d)}{m}}$

$$\text{So, } \text{Rad}(\mathcal{F}_1) \leq B_{1,\infty} \sqrt{\frac{2 \ln(2d)}{m}}$$

Now, consider $\text{Rad}(\mathcal{F}_2)$.

$$\text{Rad}(\mathcal{F}_2) = \mathbb{E}_{\mathcal{S}} \left[\sup_{h \in \mathcal{F}_2} \frac{1}{m} \sum_{i=1}^m \sigma_i h(x_i) \right]$$

$$= \mathbb{E}_{\mathcal{S}} \left[\sup_{h \in \mathcal{F}_2} \frac{1}{m} \sum \sigma_i \sigma(W_2 \langle W_1, x_i \rangle) \right]$$

$$\leq \mathbb{E}_{\mathcal{S}} \left[\sup \frac{1}{m} \sum \sigma_i W_2 \langle W_1, x_i \rangle \right] \text{ by contraction.}$$

Now, what is $W_2 \langle W_1, x_i \rangle$?

This is $g(x) := WX$ -affine transform.

Affine transform is bounded by its norm. Therefore we can see it as

$$\text{Rad}_S(\mathcal{F}_\ell) \leq \text{Rad}(W \circ \mathcal{F}_{\ell-1}) \text{ where}$$

W is B_ℓ -Lipschitz. Therefore,

$$\text{Rad}_S(\mathcal{F}_\ell) \leq \text{Rad}(W \circ \mathcal{F}_{\ell-1}) =$$

$$B_\ell \text{Rad}(\mathcal{F}_{\ell-1}) \text{ Having that } \text{Rad}(\mathcal{F}_\ell) \leq \chi_B \sqrt{\frac{2 \ln(2d)}{m}}$$

$$\text{Therefore, } \boxed{\text{Rad}(\mathcal{F}_n) \leq \left(\prod_{i=1}^n B_i \right) \chi_\infty \sqrt{\frac{2 \ln(2d)}{m}}}$$

Since $\sigma(z) = \frac{1}{1+e^{-z}}$ is also

1-Lipschitz the result should be the

same.

N4. a)

$$\|W_2\| \leq 20 \quad \text{So, } B=20.$$

Then log loss: $\ln(1 - \exp(-y \langle w, x \rangle))$

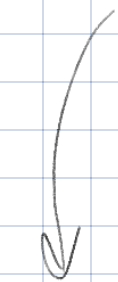
$$\nabla l = \frac{-y(x) \exp(-y \langle w, x \rangle)}{1 + \exp(-y \langle w, x \rangle)}$$

$$\|\nabla l\| \leq \max_i \|x_i\|_2 \quad \text{So, } \rho = \max_i \|x_i\|_2$$

Therefore log loss is $\max \|x_i\|_2$ Lipschitz.

Then, having $\|W\|=20$, we have

$$\eta = \sqrt{\frac{B^2}{\max \|x\|^2 T}} = \sqrt{\frac{400}{\max \|x_i\|^2 T}}$$



got from Shai SGP page.

N 4 b, c

in the CODE-HW.

NS \sim 3 days