

## Week 5 - Lecture 24

Lemma :- [When using FoReL]

$$f_t(w_t) - f_t(w_{t+1}) \leq \frac{L_t^2}{\sigma} \quad \leftarrow \begin{array}{l} \text{Lipschitz constant} \\ \text{for function } f_t \end{array}$$

$\nwarrow$   $\sigma$ -strongly convex for regularizer

Proof :-

$$\forall t, F_t(w) = \sum_{i=1}^{t-1} f_i(w) + R(w)$$



this will be  $\sigma$ -strongly convex as:

$f_i(w)$  is convex

$R(w)$  is  $\sigma$ -strongly convex

When a  $\sigma$ -strongly convex function is added to a convex function then the resulting function becomes  $\sigma$ -strongly convex.

Update rule of FoReL:

$$w_t = \underset{w}{\operatorname{argmin}} F_t(w)$$

Since  $F_t(w)$  is  $\sigma$ -strongly convex

$$\therefore F_t(w_{t+1}) \geq F_t(w_t) + \frac{\sigma}{2} \|w_t - w_{t+1}\|^2 \quad \text{--- (i)}$$

↖  
already discussed  
property of  $\sigma$ -strongly  
convex function

$$\therefore F_{t+1}(w_t) \geq F_{t+1}(w_{t+1}) + \frac{\sigma}{2} \|w_t - w_{t+1}\|^2 \quad \text{--- (ii)}$$

Adding (i) & (ii)

$$\begin{aligned} F_{t+1}(w_t) - F_t(w_t) + F_t(w_{t+1}) - F_{t+1}(w_{t+1}) \\ \geq \sigma \|w_t - w_{t+1}\|^2 \end{aligned}$$

$$\Rightarrow f_t(w_t) - f_t(w_{t+1}) \geq \sigma \|w_t - w_{t+1}\|^2 \quad \text{--- (iii)}$$

[Using the defn of  $F_t(w)$ ]

$$f_t(w_t) - f_t(w_{t+1}) \leq L_t \|w_t - w_{t+1}\| \quad \text{--- (iv)}$$

[Applying the Lipschitzness of the function]

Thus we have lower & upper bound of

$$f_t(w_t) - f_t(w_{t+1})$$

Thus we have:

$$\sigma \|w_t - w_{t+1}\|^2 \leq L_t \|w_t - w_{t+1}\|$$

$$\Rightarrow \|w_t - w_{t+1}\| \leq L_t / \sigma \quad \text{--- (v)}$$

Substituting this back in (iv), we have

$$f_t(w_t) - f_t(w_{t+1}) \leq L_t^2 / \sigma$$

Thus Lemma proved.

Using this we can now write the Theorem:

Theorem: - Let  $f_1, f_2, \dots, f_n$  are convex function  
s.t.  $f_t$  is  $L_t$ -Lipschitz w.r.t.  $\|\cdot\|$ .

Then if FoReL is used with a  $\sigma$ -strongly convex  
w.r.t. same norm then :

$$\text{Regret}(n, u) \leq R(u) - \min_{v \in S} R(v) + \frac{n L^2}{\sigma}$$

---

This is because :

We know :

$$\text{Regret}(n, u) \leq R(u) - R(w_1) + \sum_{t=1}^n f_t(w_t) - f_t(w_{t+1})$$

$\uparrow$   
This is equivalent to  
 $\min_w R(w)$

$\rightarrow$  from the Lemma we have :

$$\sum_{t=1}^n f_t(w_t) - f_t(w_{t+1}) = \sum_{t=1}^n L_t^2 / \sigma$$

Now if  $f_t$ 's have the same Lipschitz constant  
then:

$$= nL^2/\sigma$$

However if they are different

$$= \sum_{t=1}^n L_t^2 / \sigma$$

$$= n \left( \frac{\sum L_t^2}{n} \right) / \sigma$$

Multiplying &  
dividing by  
 $n$

If we assume the  $\frac{\sum L_t^2}{n} = L^2$ , then:

$$= nL^2/\sigma$$

↑ this needs  
to be included in  
the theorem when  
stating it

Regularizers:

$$1) \quad R(u) = \frac{1}{2} \|w\|_2^2 \quad \text{for } \forall u \in \mathbb{R}^d$$

This is 1-strongly convex with  $l_2$ -norm

To check this:

$$\langle \nabla^2 R(w) x, x \rangle \geq \sigma \|x\|^2$$

$$\text{Now } R(u) = \frac{1}{2\eta} \|w\|_2^2$$

is  $\frac{1}{\eta}$ -strongly convex with  $l_2$ -norm

$$2) R(u) = \sum_{i=1}^d u_i \log u_i$$

$$u \in S = \{w, w_i > 0, \sum w_i = 1\} \quad (\text{probability space})$$

$\uparrow$   
 $l_1$ -norm

$\therefore$  Entropy regularizer is 1-strongly convex w.r.t  $l_1$ -norm

if however  $u \in S = \{w, w_i > 0, \sum w_i \leq B\}$

then it is  $\frac{1}{B}$ -strongly convex w.r.t  $l_1$ -norm

Now to find : the bounds when using these regularizers.