

Assignment 5

Q.1 : Given : Linear convex optimization problem where $f_t(w) = \langle w_t, z_t \rangle$ where $z_t \in [0, 1]^d \forall t$ and $S = \{w : \|w\|_1 = 1, w \geq 0\}$.

Update rule for Weighted Majority :

$$w_i^{t+1} = w_i^t \exp(-\eta Z_{ti}) \text{ for the } i\text{-th expert}$$

————— (1)

ForEL update Rule :

$$\forall t, w_t = \underset{w \in S}{\operatorname{argmin}} \sum_{i=1}^{t-1} f_i(w) + R(w) \quad \text{————— (2)}$$

Entropy Regularizer :

$$R(w) = \frac{1}{\eta} \sum_{k=1}^d w_k \log w_k$$

Thus ForEL update rule with Entropy Regularizer

$$w_t = \underset{w \in S}{\operatorname{argmin}} \sum_{i=1}^{t-1} f_i(w) + \frac{1}{\eta} \sum_{k=1}^d w_k \log w_k \quad \text{————— (3)}$$

Given $f_t(w) = \langle w_t, z_t \rangle$

$$\begin{aligned} \text{Let } F_t &= \sum_{i=1}^t f_t(w) + R(w) \\ &= \sum_{i=1}^{t-1} \langle w, z_i \rangle + \frac{1}{\eta} \sum_{k=1}^d w_k \log w_k \end{aligned}$$

Differentiating w.r.t. w

$$F'_t = \sum_{i=1}^t z_i + \frac{1}{\eta} \sum_{k=1}^d [\log(w_k) + 1]$$

$$F'_t = \sum_{i=1}^t z_i + \frac{d}{\eta} \sum_{k=1}^d \log(w_k)$$

Setting $F'_t = 0$ [as $w = \operatorname{argmin} F_t$]

$$\Rightarrow 0 = \sum_{i=1}^t z_i + \frac{d}{\eta} \sum_{k=1}^d \log w_k$$

$$\Rightarrow \sum_{k=1}^d \log(w_k) = -\frac{\eta}{d} \sum_{i=1}^t z_i$$

Considering for one arm at round t , we have:

$$\log(w_t) = -\eta z_{tk}$$

$$\Rightarrow w_t = \exp(-\eta z_{tk})$$

$$\Rightarrow \underline{w_t = w_{t-1} \exp(-\eta z_{(t-1)k})} \quad \text{--- (5)}$$

Hence the update rule for FoRel with

Entropy Regularizer is equivalent to the update rule of weighted majority.

Regret of Weighted Majority

$$\begin{aligned} \text{Regret}(n) &= \sum_{t=1}^n \langle w_t, z_t \rangle - \min_{i \in [d]} \sum_{t=1}^n V_{ti} \\ &\leq \sqrt{2n \log d} \end{aligned} \quad \text{--- (6)}$$

We know the Theorem :

Let f_1, \dots, f_n be a sequence of convex functions s.t. f_t is L_t -Lipschitz with respect to norm $\|\cdot\|$. Let L be such that $\frac{1}{n} \sum_{t=1}^n L_t^2 \leq L^2$.

If FoReL is run on the sequence with a regularizer which is σ -strongly convex w.r.t. the same norm. Then, $\forall u \in S$,

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

--- (7)

Thus for FoReL with Entropy Regularizer

[Entropy Regularizer is $\frac{1}{\eta}$ - strongly convex]

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

$$\leq R(u) + \max(-R(u)) + n\eta L^2$$

$$\begin{aligned} -R(u) &= \frac{1}{\eta} \sum_{i=1}^d u_i \log \frac{1}{u_i} \\ &\leq \frac{1}{\eta} \log d \sum_{i=1}^d 1/u_i \\ &\leq \frac{1}{\eta} \log d \end{aligned}$$

$$\leq R(u) + \frac{1}{\eta} \log d + n\eta L^2$$

Now Given that let U be a set of unit vectors

Thus $U \in \{e_1, e_2, \dots, e_d\}$ where

$$e_1 = \{1, 0, 0, \dots, 0\}$$

$$e_2 = \{0, 1, 0, \dots, 0\}$$

$$\vdots$$
$$e_d = \{0, 0, 0, \dots, d\}$$

Now considering u to be any e_i , we have :

$$\frac{1}{\eta} \sum_{i=1}^d u_i \log u_i = 0$$

Thus the Regret simplifies to :

$$\text{Regret}(n, u) \leq \frac{1}{\eta} \log d + L^2 n \eta$$

Setting $\eta = \frac{\sqrt{\log d}}{L \sqrt{2n}}$ we get

$$\text{Regret}(n, u) \leq L \sqrt{2n \log d} \quad \text{--- (8)}$$

For prediction with expert advice $L=1$

$$\therefore \text{Regret}(n, \text{FoReL}, u) \leq \sqrt{2n \log d} \quad \text{--- (9)}$$

which is similar to the regret bound obtained for weighted majority.

Q.2: Given: For any differentiable function

$R: \mathbb{R}^d \rightarrow \mathbb{R}$, for vectors w and u

Bregman Distance is defined as:

$$D_R(w||u) = R(w) - R(u) - \langle \nabla R(u), w - u \rangle$$

To find: The Bregman divergence of $R = \frac{1}{2} \|u\|_2^2$

$$R = \frac{1}{2} \|u\|_2^2$$

$$\nabla R(u) = u$$

$$D_R(w||u) = \frac{1}{2} \|w\|_2^2 - \frac{1}{2} \|u\|_2^2 - \langle u, w - u \rangle$$

$$= \frac{1}{2} \sum_i w_i^2 + \frac{1}{2} \sum_i u_i^2 - \sum_i (\langle w, u \rangle - \langle u, u \rangle)$$

$$= \frac{1}{2} \sum_i \langle w, w \rangle + \frac{1}{2} \sum_i \langle u, u \rangle - \sum_i \langle w, u \rangle + \sum_i \langle u, u \rangle$$

$$= \frac{1}{2} \sum_i \langle w, w \rangle - \sum_i \langle w, u \rangle + \frac{1}{2} \sum_i \langle u, u \rangle$$

$$\Rightarrow D_R(w||u) = \frac{1}{2} \|w - u\|_2^2$$
