

Mehryar Mohri  
Advanced Machine Learning 2024  
Courant Institute of Mathematical Sciences  
Homework assignment 1  
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## 1 Short proof of Hoeffding's lemma

Let  $X$  be a random variable with  $\mathbb{E}[X] = 0$  and  $|X| \leq 1$ . Show that for any  $t > 0$ ,  $\mathbb{E}[e^{tX}] \leq e^{t^2/2}$ . *Hint*: use the convexity of exponential to derive  $\mathbb{E}[e^{tX}] \leq \cosh(t)$ .

## 2 Small loss bound

In lecture 3, we used the bound on the regret of Randomized Weighted Majority (RWM):  $R_T \leq O(\sqrt{L_T^{\min} \log N})$ , assuming  $L_T^{\min} \neq 0$ . Here, you are asked to give a proof. Using the proof given in Lecture 1 for the regret of RWM and the inequality  $\mathcal{L}_T \leq \frac{\log N}{1-\beta} + (2-\beta)\mathcal{L}_T^{\min}$ , show that for a suitable choice of  $\beta$ , we have  $R_T \leq 4\sqrt{\mathcal{L}_T^{\min} \log N}$ .

## 3 Weighted online-to-batch

Let  $\ell$  be a loss function convex with respect to its first argument and bounded by one. Let  $h_1, \dots, h_T$  be the hypotheses returned by an on-line learning algorithm  $\mathcal{A}$  with regret  $R_T$  when sequentially processing  $(x_t, y_t)_{t=1}^T$ , drawn i.i.d. according to some distribution  $\mathcal{D}$ .

1. Fix some arbitrary non-negative weights  $q_1, \dots, q_T$  summing to one. Then, show that with probability at least  $1-\delta$ , the hypothesis  $h = \sum_{t=1}^T q_t h_t$  satisfies each of the following inequalities:

$$\begin{aligned} \mathbb{E}_{(x,y) \sim \mathcal{D}} [\ell(h(x), y)] &\leq \sum_{t=1}^T q_t \ell(h_t(x_t), y_t) + \|q\|_2 \sqrt{2 \log(1/\delta)} \\ \mathbb{E}_{(x,y) \sim \mathcal{D}} [\ell(h(x), y)] &\leq \inf_{h \in \mathcal{H}} \mathbb{E}_{(x,y) \sim \mathcal{D}} [\ell(h(x), y)] + \frac{R_T}{T} \\ &\quad + \|q - u\|_1 + 2\|q\|_2 \sqrt{2 \log(1/\delta)}, \end{aligned}$$

where  $q$  is the vector with components  $q_t$  and  $u$  the uniform vector with all components equal to  $1/T$ .

2. Here, we seek to prove a bound that holds uniformly for all weight vectors  $q$  in some set. To do so, we consider a weight vector  $p$  that serves as a *reference*. A natural reference in this context could be for example the uniform distribution. Show that, for any  $\delta > 0$ , the following holds with probability at least  $1 - \delta$  for all  $q \in \{q: \|q - p\|_1 < 1\}$ :

$$\begin{aligned} \mathbb{E}_{(x,y) \sim \mathcal{D}} [\ell(h(x), y)] &\leq \sum_{t=1}^T q_t \ell(h_t(x_t), y_t) + 2\|q - p\|_1 \\ &\quad + (\|q\|_2 + 2\|q - p\|_1) \left[ 2\sqrt{\log \log_2 \frac{2}{1 - \|q - p\|_1}} + \sqrt{2 \log \frac{2}{\delta}} \right]. \end{aligned}$$

*Hint:* consider the first inequality proven above for a fixed weight vector  $q^k$  and approximation error  $\epsilon_k$ , for any  $k \geq 0$ . Show that the inequality can be extended to hold uniformly for all  $k \geq 0$  if you choose  $\epsilon_k = \epsilon + \sqrt{2 \log(k + 1)}$ .

## 4 Coarse correlated equilibrium

Consider a finite normal form game with  $p < +\infty$  players and finite action sets  $\mathcal{A}_k$ ,  $k \in [1, p]$ . Show that if each player plays an external regret minimization strategy that has regret at most  $\epsilon$ , then the empirical average of the players (product) distributions:  $\mathbf{p} = \frac{1}{T} \sum_{t=1}^T \mathbf{p}^t$ , where  $\mathbf{p}^t = \prod_{k=1}^p \mathbf{p}_k^t$ , is an  $\epsilon$ -approximate coarse correlated equilibrium, that is, for all  $k \in [1, p]$ , for all  $a_k \in \mathcal{A}_k$  and all  $a'_k \in \mathcal{A}_k$ ,

$$\mathbb{E}_{\mathbf{a} \sim \mathbf{p}} [u_k(a'_k, a_{-k})] \leq \mathbb{E}_{\mathbf{a} \sim \mathbf{p}} [u_k(a_k, a_{-k})] + \epsilon.$$