# Online Computation, Ex 3.

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**ex1.** Consider the experts setting with gains: $g_{i,t} \in [0,1]$ is the gain of expert $i$ at step $t$. Hedge updates:

$$P_{i,t+1} = \frac{e^{\eta G_{i,t}}}{\sum_j e^{\eta G_{j,t}}}$$

where $G_{i,t} = \sum_{s \leq t} g_{i,t}$. Prove that the regret of Hedge at time $T$ is $O\left(\sqrt{T \log n}\right)$, for a good choice of the learning rate $\eta$, against the adaptive adversary.

**Solution.** Let $g_t$ be the random variable which count the gain at time step $t$ and by $G_t = \sum_t^T g_t$. Recall that for any pair of random variable $X, Y$ such that $X \geq Y$ it holds that $\mathbf{E}[X] \geq \mathbf{E}[Y]$. Also notice that for $x$ restricted to some range $[-r, r]$ there are constants $c_+, c_-$ depeand on $r$ such that $c_- x^2 \leq e^x - 1 - x \leq c_+ x^2$. Namely, the exponent is bounded by quaderic approximation (second tylor series order). By the montenus property of the expection, for any random variable $X$ that maps to bounded range $[-r, r]$ it holds that:

$$c_- \mathbf{E}\left[x^2\right] \leq \mathbf{E}\left[e^x - x - 1\right] \leq c_+ \mathbf{E}\left[x^2\right]$$

Define the potential $\psi(t) = \sum_j e^{\eta G_{i,t}}$ and notice that:

1. $\frac{\psi(t+1)}{\psi(t)} = \mathbf{E}\left[e^{\eta g_t}\right]$ relatives to the distribution $P_{i,t+1}$.

2. $\psi(t) \geq e^{\eta G_{t,j}}$ for any $t$ and $j$ in particular the $j$ which maximizes the gain.

3. $\frac{\psi(t+1)}{\psi(t)} \leq e^{\eta}$

4. $e^{\eta G_{t,j}} \leq e^{\eta} \psi(0)$ for any $j$.

Therefore we obtain that:

$$\begin{aligned}
&\psi(T) = \frac{\psi(T)}{\psi(0)} \psi(0) = \prod^T \frac{\psi(t+1)}{\psi(t)} \psi(0) \\
&n \prod_t^T \mathbf{E}\left[e^{\eta g_t}\right] \leq n \prod_t^T \mathbf{E}\left[1 + \eta g_t + c_{\pm} (\eta g_t)^2\right] \\
&n \prod_t^T 1 + \mathbf{E}\left[\eta g_t + c_{\pm} (\eta g_t)^2\right] \leq n \prod_t^T e^{\mathbf{E}\left[\eta g_t + c_{\pm} (\eta g_t)^2\right]} \leq \\
&n e^{\mathbf{E}\left[\sum \eta g_t + c_{\pm} (\eta g_t)^2\right]} \leq n e^{\mathbf{E}\left[\sum \eta g_t\right] + \mathbf{E}\left[c_{\pm} (\eta g_t)^2\right]}
\end{aligned}$$

by the fact that $e^x$ is positive function we have that $\psi(t) \geq e^{\eta \max_j G_{i,j}}$. In addition:

$$\begin{aligned}
&\frac{\psi(t+1)}{\psi(t)} = \psi(t)^{-1} \sum_j e^{\eta G_{j,t} + \eta g_{j,t+1}} \\
&= \mathbf{E}\left[e^{\eta g_t}\right] \leq e^{\mathbf{E}[\eta g_t]} \Rightarrow \psi(T) \leq \psi(0) e^{\eta \mathbf{E}[G_t]} \\
&\psi(t+1) = \sum_j e^{\eta G_{j,t+1}} = \sum_j e^{\eta G_{j,t} + \eta g_{j,t+1}} \\
&\leq \sum_j e^{\eta G_{j,t}} \left(1 + c_1 \eta g_{j,t+1}\right) = \psi(t) + c_1 \eta \psi(t) \mathbf{E}\left[g_{t+1}\right] \\
&\leq e^{\eta} (1 + c_2) \psi(t) \mathbf{E}\left[g_{t+1}\right] \\
&\leq \prod_t \left(1 + c_1 \mathbf{E}\left[g_t\right]\right) (\psi(0)) \leq e^{c_2 \mathbf{E}\left[\sum g_t\right]} \psi(0) \\
&\leq e^{c_2 \mathbf{E}[G_t]} \cdot e^{\eta} n
\end{aligned}$$

So after $T$ steps, by taking the logaritm of both sides, we obtain that the regret is bounded by $R_T \leq$.

**ex2.** Show a lower bound of $\Omega\left(\sqrt{T}\right)$ in the experts setting on the regret of any online algorithm against the oblivious adversary.

**Solution.** solution.

**ex3.** Consider a system of linear inequalities $Ax \geq b$, where $A \in [0, \infty]^{m \times n}, b \in [0, \infty]^m$, and unknown $x \in [0, \infty]^n$. (we are seeking a non-negative solution). An $\varepsilon$-approximate solution $x \geq 0$ satisfies $Ax \geq b - \varepsilon \mathbf{1}$. Suppose we have an efficient procedure for following problem: Given $p \in [0,1]^m, \sum_{i \in [m]} p_i = 1$, decide if exists $x \geq 0, p^{\top} A x \geq p^{\top} b$. Show how to find an $\varepsilon$-approximate solution to $Ax \geq b$. Analyze the run-time.

**Solution.** solution.

**ex4.** Recall that we showed, for $EXP$ updates, that w.p $1 - \delta$

$$RT \leq \beta n T + \gamma T + (1 + \beta) \eta + \frac{\ln\left(\delta^{-1} n\right)}{\beta} + \frac{\ln n}{\eta}$$

Infer that for the right choice of $\beta, \gamma, \eta$

$$\mathbf{E}\left[R_T\right] = O\left(\sqrt{T n \ln n}\right)$$