IE613: Online Machine Learning **Jan-Apr 2017**

Assignment 2: March 17

Instructions: *You are free to code in Python/Matlab/C/R. Discussion among the class participants is highly encouraged. But please make sure that you understand the algorithms and write your own code. Submit the code by 24th March.*

Question 1 (Full information setting) *Consider the problem of prediction with expert advice with $d = 10$. Assume that the losses assigned to each expert are generated according to independent Bernoulii distributions. The adversary/environment generates loss for experts 1 to 8 according to $Ber(.5)$ in each round. For the 9th expert, loss is generated according to $Ber(.5 - \Delta)$ in each round. The losses for the 10th expert are generated according to different Bernoulii random variable in each round– for the first $T/2$ rounds, they are generated according to $Ber(0.5+\Delta)$ and the remaining $T/2$ rounds they are generated according to Bernoulii random variable $Ber(0.5-2\Delta)$. $\Delta = 0.1$ and $T = 10^6$. Generate (pseudo) regret values for different learning rates for each of the following algorithms. The averages should be taken over atleast 50 sample paths (more is better). Display the 95% confidence intervals for each plot. Select the best value for the learning rate η.*

- *Weighted Majoirty algorithm. Set $\eta = c\sqrt{2\log(d)/T}$ and vary c from $[0.1\ 2.1]$ in steps of size 0.2.*
- *Follow the Regularized Leader (FTRL) with linear loss functions and negative entropy as the regularizer. In round $t = 1, 2, \cdots, T$, the linear function is $f_t(w) = w'v_t$, where $v_t \in \{0, 1\}^d$ is loss vector generated in round t. What is the optimal η? Let the optimal value be η^*. Set $\eta = c\eta^*$ and vary c from $[0.1\ 2.1]$ in steps of size 0.2.*

Question 2 (Bandit setting) *Consider the problem of multi-armed bandit with $K = 10$ arms. Assume that the losses are generated as in Question 1. For each of the following algorithms generate (pseudo) regret vs T plots. The averages should be taken over atleast 50 sample paths (more is better). Display the 95% confidence interval for each plot. Select the best values for parameters, η, γ and β.*

- *EXP3. Set $\eta = c\sqrt{2\log(K)/KT}$ and vary c from $[0.1\ 2.1]$ in steps of size 0.2.*
- *EXP3.P. Set $\eta = c\sqrt{2\log(K)/KT}$, $\beta = \eta$, $\gamma = K\eta$, and vary c from $[0.1\ 2.1]$ in steps of size 0.2.*
- *EXP-IX. Set $\eta = c\sqrt{2\log(K)/KT}$, $\gamma = \eta/2$, and vary c from $[0.1\ 2.1]$ in steps of size 0.2.*

Question 3 *Comment on the performance of EXP, EXP3.P and EXP-IX. Which one performs better? Can you think of a your own method which performs better than any of the above methods. Give pseudo-code of your algorithm and compare its performance with others.*