

# MLT Homework 8

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## Question 1

The Aggregating Algorithm plays  $w_1^k = 1/K$  and updates as

$$w_{k+1}^k = \frac{w_t^k e^{-l_t^k}}{\sum_{j=1}^K w_t^j e^{-l_t^j}}$$

Let us define the Kullback-Leibler divergence aka relative entropy (notion of distance between probability distributions) from  $p \in \Delta_K$  to  $q \in \Delta_K$  by

$$KL(p,q) = \sum_{k=1}^K p_k \ln \frac{p_k}{q_k}$$

Fix  $w_t \in \Delta_K$  and  $l_t \in \mathbb{R}^K$ . Consider the minimisation problem

$$\min_{w \in \Delta_K} w^T l_t + KL(w, w_t) \tag{1}$$

### Subquestion 1.1

Show that the minimiser of problem (1) is  $w_{t+1}$ .

**Solution**

### Subquestion 1.2

Show that the value of problem (1) is the mix loss.

**Solution**

## Question 2

We saw in the lecture that the Hedge algorithm (for the dot-loss game) with learning rate  $\eta = \sqrt{\frac{8 \ln K}{T}}$  has regret after  $T$  rounds bounded by  $\sqrt{T/2 \ln K}$ . In practice, we may not know  $T$  in advance, or we may even desire an algorithm that has good guarantees for all  $T$  simultaneously, i.e. that keeps on operating forever.

Prove that the overall accumulated regret of Hedge with this scheme is bounded above by a universal constant times  $\sqrt{T \ln K}$ . (Your argument should work for  $T$  that are not a power of 3).

**Solution**

## Question 3

Consider the  $K = 2$  expert version of the  $T$ -round dot loss game (Definition 2). In this exercise we will prove that the worst-case expected regret is at least of order  $\sqrt{T}$ . Consider an adversary that for each  $t = 1, \dots, T$  assigns loss vector  $l_t = (0, 1)$  or  $l_t = (1, 0)$  i.i.d uniformly at random.

### Subquestion 3.1

Show that the expected loss of any learner is  $T/2$ .

**Solution**

### Subquestion 3.2

Show that  $2(1/2 - l_t^k)$  is Rademacher for each  $k \in \{1, 2\}$ .

**Solution**

### Subquestion 3.3

Show that  $\sum_{t=1}^T (1/2 - l_t^2) = -\sum_{t=1}^T (1/2 - l_t^1)$ .

**Solution**

### Subquestion 3.4

Argue that the expected loss of the best expert is bounded above by  $\mathbb{E}[\min_k \sum_{t=1}^T l_t^k] \leq T/2 - c\sqrt{T}$  for some  $c > 0$ . You can use the following fact. Let  $X_1, \dots, X_T$  be

*i.i.d Rademacher random variables. Then*

$$\mathbb{E} \left[ \sum_{t=1}^T X_t \right] \in \left[ \sqrt{\frac{2(T-1)}{\pi}}, \sqrt{\frac{2(T+1)}{\pi}} \right].$$

**Solution**