

Algorithms and Uncertainty

Summer Term 2020

Exercise Set 8

Exercise 1: (3+2 Points)

Recall the regret definition from the lecture: $\text{Regret}^{(T)} = L_{\text{Alg}}^{(T)} - \min_i \sum_{t=1}^T \ell_i^{(t)}$.

We want to understand the order of minimum and sum in the second term. Therefore, work on the following tasks.

- (a) Use Yao's principle to show that for every (randomized) algorithm there is a sequence $\ell^{(1)}, \dots, \ell^{(T)}$ such that $L_{\text{Alg}}^{(T)} \geq (1 - \frac{1}{n}) T$ but $\sum_{t=1}^T \min_i \ell_i^{(t)} = 0$.
- (b) Discuss the importance of the order of sum and minimum in the regret definition using your results from (a).

Exercise 2: (4 Points)

We consider a generalization of the algorithm *Weighted Majority* for classifiers with k different classes. (The case covered in the lecture, binary classification, is $k = 2$.) In each step, the algorithm chooses a class, which is recommended by the largest number of classifiers (so the class has a plurality).

Show that this algorithm makes at most $(2 + 2\eta) \min m_i + 2 \ln n / \eta$ errors, where m_i is the number of errors of classifier i .

Exercise 3: (4 Points)

Consider the modified update rule for Multiplicative Weights that sets $w_i^{(t+1)} = w_i^{(t)} \cdot (1 - \ell_i^{(t)} \eta)$. Show that Theorem 16.3 still holds.

Exercise 4: (4 Points)

Show that every no-regret algorithm in the experts setting has to be randomized. Consider the case $n = 2$ and for every deterministic algorithm construct a sequence such that $L_{\text{Alg}}^{(T)} = T$ and $\min_i L_i^{(T)} \leq \frac{T}{2}$.