

## 15-251: Great Theoretical Ideas In Computer Science

### Recitation 14 Solutions

#### Important concepts from lecture

- A **Nash equilibrium** is a choice function from players to strategies such that no one player will benefit from changing their strategy.
- The **social cost** of a given solution (strategy choice function) is the sum of the costs to all players of the resulting game outcome.
- The **price of anarchy** is a metric to compare the social costs of “selfish” play (Nash equilibria) and some form of “cooperation” (the social-cost-optimal solution).
- A **consistent hypothesis** with respect to a set  $S$  of labelled points is any hypothesis that labels every point in  $S$  correctly.
- A **PAC learning algorithm** is one that, for any  $\epsilon, \delta > 0$ , any distribution  $D$ , and any  $m_0(\epsilon, \delta)$  training points distributed according to  $D$ , has probability at least  $1 - \delta$  of arriving at a hypothesis whose error with respect to  $D$  is at most  $\epsilon$ .

#### The Only Winning Move

Consider the two-player game where each player, without knowledge of the other’s choice, chooses a strategy from  $S = \{0, 1\}$ . Player 1 wins \$100 iff they both choose the same strategy, and Player 2 wins \$100 otherwise.

a) Show that there is no Nash equilibrium.

b) How can we modify  $S$  to preserve the nature of the game yet make it so that there will be at least one Nash equilibrium? (Hint: imagine actually playing this game, perhaps repeatedly. How can we make the given model more realistic?)

c) Characterize the set of Nash equilibria after this modification.

a)  $(0, 0), (1, 1)$  are not equilibria because player 2 would benefit from changing their strategy. Likewise,  $(0, 1), (1, 0)$  are not equilibria because player 1 would benefit from changing their strategy.

b) We can extend  $S$  to include probabilistic mixtures of strategies if we let  $S' = [0, 1]$  where the strategy  $r$  represents playing 1 with probability  $r$  and playing 0 with probability  $1 - r$ .

c)  $(0.5, 0.5)$  turns out to be the only Nash equilibrium. With a bit of casework we can verify that neither party benefits from strategy-switching.

To prove uniqueness: AFSOC that some other NE  $(a, b)$  exists. If  $a > 0.5$ , then player 2 would benefit from lowering their strategy to 0. (If player 2’s strategy is already 0, then player 1 would benefit from switching to also play 0.) If  $a < 0.5$ , then player 2 would benefit from raising their strategy to 1. (If player 2’s strategy is already 1, then player 1 would benefit from switching to also play 0.) In the last case, where  $a = 0.5 \neq b$ , player 1 would benefit from switching to play 0 if  $b < 0.5$  or 1 if  $b > 0.5$ .

## Alg-chemistry

In lecture we saw that, if we're given an algorithm that always finds a consistent hypothesis, we can construct a PAC learning algorithm by finding a hypothesis consistent with some  $m_0(\epsilon, \delta)$  points sampled from the input distribution.

Let's try going the other way: given a set  $S$  of labelled points, some  $\delta > 0$ , and a PAC learning algorithm  $A$  that may not always output a consistent hypothesis, devise a procedure to find a hypothesis that is consistent with  $S$  with probability at least  $1 - \delta$ .

Given  $S$ , let  $D'$  be the uniform distribution over points in  $S$ . Choose  $\epsilon' < \frac{1}{|S|}$  because any hypothesis having error at most  $\epsilon'$  with respect to  $D'$  must actually have error 0. (This is because mislabelling any one example in  $S$  will result  $\frac{1}{|S|}$  error.)

Then we can simply set  $\delta' = \delta$ , sample  $m_0(\epsilon', \delta')$  samples from  $D'$ , and use our PAC algorithm  $A$ . With probability at least  $1 - \delta' = 1 - \delta$ , the hypothesis output will be consistent with  $S$ .

## Intersection classes

Let  $C_1$  and  $C_2$  be two concept classes. Define the "intersection class"

$$C = \{c \mid \exists c_1 \in C_1, c_2 \in C_2. \forall x \in X. c(x) = + \iff c_1(x) = c_2(x) = +\}$$

which is to say that every concept  $c \in C$  is the intersection of some  $c_1 \in C_1$  and  $c_2 \in C_2$ . Recall that for any set of examples  $S$  and any concept class  $C'$ ,  $\pi_{C'}(S)$  is the number of ways of labeling examples in  $S$  using concepts from  $C'$ . Let  $\pi_{C'}(m)$  be the max of  $\pi_{C'}(S)$  over all  $m$ -sized example sets  $S$ , and show that  $\pi_C(m) \leq \pi_{C_1}(m) \cdot \pi_{C_2}(m)$ .

Take any set  $X$  of  $m$  points. Let  $k_1, k_2$  be the number of distinct subsets of  $X$  labelled  $+$  by the concepts in  $C_1$  and  $C_2$  respectively. Note that  $k_1 \leq \pi_{C_1}(X) \leq \pi_{C_1}(m)$  and  $k_2 \leq \pi_{C_2}(X) \leq \pi_{C_2}(m)$ . Now the subsets of  $X$  that are labelled  $+$  by the concepts in  $C$  are formed by intersections of the subsets of  $X$  labelled  $+$  by the concepts in  $C_1$  and the subsets of  $X$  labelled  $+$  by the concepts in  $C_2$ . So the number of distinct subsets of  $X$  labelled  $+$  by the concepts in  $C$  satisfies  $\pi_C(X) \leq k_1 \cdot k_2 \leq \pi_{C_1}(m) \cdot \pi_{C_2}(m)$ . Since this holds for all  $X$  of size  $m$ , we conclude that  $\pi_C(m) \leq \pi_{C_1}(m) \cdot \pi_{C_2}(m)$ .