15780: GRADUATE AI (SPRING 2018)

Practice Midterm 1

March 1, 2018

Heuristic Search	20	
Learning Theory	25	
Optimization and ML	30	
Linear Programming	25	
Total	100	

1 Heuristic Search (20 points)

Consider the following search problem. There is a set of *operations* $O = \{o_1, \ldots, o_n\}$, and a set of *conditions* $C = \{C_1, \ldots, C_m\}$. Each operation $o_i \in O$ has a set of *preconditions* $P_i \subseteq C$, and a set of *effects* $E_i \subseteq C$. A state is defined by a subset of conditions $S \subseteq C$. An operation $o_i \in O$ can be applied at state S if and only if $P_i \subseteq S$, and it leads to the state $S \cup E_i$. The goal state is C, i.e., the state that contains all conditions. The initial state is the empty set (so initially only operations o_i that have an empty P_i can be applied).

We define the following heuristic function h for this search problem. Given a state S, h(S) computes the optimal path to the goal state, in the modified problem where every operation o_i is replaced with the operation o'_i , which has the same set of effects E_i , but an empty set of preconditions. Informally, any of the "old" operations can be applied at any state. (The perceptive student may have noticed that computing h(S) is equivalent to solving the Minimum Set Cover problem, that is, computing h(S) happens to be computationally hard, so this is a pretty bad heuristic.)

Prove that A^* graph search with the heuristic h is optimal (it always finds the shortest sequence of operations that leads to the goal state). You may rely on any theorem stated in class.

2 Learning Theory (25 points)

Q1. (10 pt) For a finite function class F, show that $\text{VC-dim}(F) \leq \log_2(|F|)$.

Q2. (5 pt) Give an example of an input space X and a function class F such that VC-dim $(F) = \log_2(|F|)$.

Q3. (10 pt) Give an example of an input space X and two function classes F_1 and F_2 such that VC-dim $(F_i) = 0$ for i = 1, 2, but VC-dim $(F_1 \cup F_2) = 1$.

3 Optimization and ML (30 points)

Q1. (10 pt) Consider the regression problem of minimizing the sum of absolute losses using a linear hypothesis function, that is m

$$\underset{\theta \in \mathbb{R}^n}{\text{minimize}} \quad \sum_{i=1}^m \ell(h_\theta(x^{(i)}), y^{(i)}) \tag{1}$$

where $\ell : \mathbb{R} \times \mathbb{R} \to \mathbb{R}_+$ is given by $\ell(\hat{y}, y) = |\hat{y} - y|$ and $h_{\theta}(x) = \theta^T x$. Show that this is a convex optimization problem in θ .

Q2. (10 pt) Prove that we can find the solution of the absolute loss linear regression problem by solving the following linear program

$$\begin{array}{ll} \underset{\theta \in \mathbb{R}^{n}, z \in \mathbb{R}^{m}}{\text{minimize}} & \sum_{i=1}^{m} z_{i} \\ \text{subject to} & -z_{i} \leq \theta^{T} x^{(i)} - y^{(i)} \leq z_{i} \end{array} \tag{2}$$

Q3. (10 pt) Prove that we can find the linear classifier that minimizes 0/1 loss using the following *binary integer* programming problem, for a large enough value of M.

$$\begin{array}{l} \underset{\theta \in \mathbb{R}^{n}, z \in \{0,1\}^{m}}{\text{minimize}} & \sum_{i=1}^{m} z_{i} \\ \text{subject to } y^{(i)} \theta^{T} x^{(i)} \ge 1 - z_{i} M \end{array}$$
(3)

4 Linear Programming (25 points)

4.1 Standard Form (10 points)

Recall that a linear program is in the *standard form* if it is expressed as follows:

minimize
$$c^T x$$

subject to $Ax = b$
 $x \ge 0$

with optimization variable $x \in \mathbb{R}^n$, and problem data $c \in \mathbb{R}^n$, $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$. Convert the following problem to the standard form:

maximize
$$x_1 + 2x_2$$

subject to $x_1 + 3x_2 \le 12$
 $-2x_1 - x_2 \ge -8$
 $1 \le x_1$
 $0 \le x_2 \le 4.$

Specifically, what is c, A, and b in the converted problem?

4.2 Simplex Algorithm (15 points)

The following is **part** of the simplex algorithm for solving a linear program in the standard form:

Repeat:

- 1. Given index set \mathcal{J} such that $x_{\mathcal{J}} = A_{\mathcal{J}}^{-1}b \ge 0$.
- 2. Find $j \notin \mathcal{J}$ for which $\bar{c}_j = c_j c_{\mathcal{J}}^T A_{\mathcal{J}}^{-1} A_j < 0$.
- 3. Compute step direction $d_{\mathcal{J}} = -A_{\mathcal{J}}^{-1}A_j$ and determine index to remove

 $i^{\star} = ?$

4. Update index set: $\mathcal{J} \leftarrow \mathcal{J} - \{i^*\} \cup \{j\}$.

Choose one correct answer for each of the following statements:

- **Q1.** (5 pt) In the second step of the algorithm, no $j \notin \mathcal{J}$ satisfies $c_j c_{\mathcal{J}}^T A_{\mathcal{J}}^{-1} A_j < 0$. This means [(1) a solution is found, (2) the problem is infeasible, (3) the problem is unbounded].
- **Q2.** (5 pt) In the third step of the algorithm, i^* should be set to

$$\left[(1) \underset{i \in \mathcal{J}: d_i < 0}{\arg\min} x_i/d_i, (2) \underset{i \in \mathcal{J}: d_i < 0}{\arg\max} x_i/d_i, (3) \underset{i \in \mathcal{J}: d_i \ge 0}{\arg\min} x_i/d_i, (4) \underset{i \in \mathcal{J}: d_i \ge 0}{\arg\max} x_i/d_i \right].$$

Q3. (5 pt) In the third step of the algorithm, every $i \in \mathcal{J}$ satisfies $d_i \ge 0$. This means [(1) a solution is found, (2) the problem is infeasible, (3) the problem is unbounded].