Fall 2014 Handout 18 11 November 2014

Sample Solution to Problem Set 5

1. (10 points) Single-variable linear program

Exercise 29.5-9 of text.

Answer: The dual D is to minimize sy subject to $ry \ge t$ and $y \ge 0$.

- 1. P and D are feasible and bounded: r > 0 and $s \ge 0$, or r < 0 and $t \le 0$, or r = 0 and s = 0 and t = 0.
- 2. P feasible but D infeasible: r < 0 and t > 0, or r = 0, $s \ge 0$ and t > 0.
- 3. P infeasible but D feasible: r > 0 and s < 0, or r = 0, $t \le 0$ and s < 0.
- 4. P and D both infeasible: r = 0, s < 0, t > 0.

2. (10 points) LP for single-source shortest paths

Exercise 29.2-3 of text.

Answer: Here is one linear program for the problem.

$$\max \sum_{v} d_{v}$$

$$d_{u} + w(u, v) - d_{v} \ge 0 \text{ for each edge } (u, v)$$

$$d_{s} = 0$$

$$d_{v} \ge 0 \text{ for each vertex } v$$

We claim that an optimal solution to the LP, given by $\{d_v^*: v \in V\}$ yields the shortest path distances. Let δ_v denote the shortest path weight from s to v for each v in V. Since δ_v 's are nonnegative and satisfy triangle inequality, and $\delta_s = 0$, $d_v = \delta_v, \forall v$ is a feasible solution to the LP.

We now argue that δ is the optimal solution for the LP. That is, $\delta_v = d_v^*$ for all v. Suppose not, for the sake of contradiction; i.e., $\sum_v d_v^* > \sum_v \delta_v$. Consider the shortest path tree rooted at s. Then, there must exist two vertices x and y such that x is the parent of y in the tree, $\delta_x \geq d_x^*$ and $\delta_y < d^*y$. But we know that $\delta_y = \delta_x + w(x,y)$, so this implies that $d_y^* > \delta_y = \delta_x + w(x,y) \geq d_x^* + w(x,y)$, a contradiction.

3. (20 points) Complementary slackness

Problem 29-2 of text.

Answer:

- (a) Follows from elementary calculations using the solutions for the primal and dual given in the text.
- (b) Let M be the set of j for which $\bar{x}_i > 0$ and N be the set of i for which $\bar{y}_i > 0$. Then, we have

$$\sum_{j} c_{j} \bar{x}_{j} = \sum_{j \in M} c_{j} \bar{x}_{j}$$

$$\leq \sum_{j \in M} \sum_{i} a_{ij} \bar{y}_{i} \bar{x}_{j}$$

$$= \sum_{i \in N} \left(\sum_{j \in M} a_{ij} \bar{x}_{j} \right) \bar{y}_{i}$$

$$\leq \sum_{i \in N} b_{i} \bar{y}_{i}$$

$$= \sum_{i} b_{i} \bar{y}_{i}$$

By strong duality, the two inequalities should be equalities. The only way for this to hold is to have term-by-term equality $c_j = \sum_i a_{ij}\bar{y}_i$ for $j \in M$ and $b_i = \sum_j a_{ij}\bar{x}_j$ for $i \in N$, yielding the complementary slackness conditions.

(c) Suppose \bar{x} is an optimal solution to the primal. Since the primal is feasible and bounded, so is the dual. So we have an optimal solution \bar{y} for the dual. This, together with part (b), establishes the three desired properties.

Suppose we have a feasible solution satisfying the three properties. Going through the calculations as in part (b), we obtain that $\sum_j c_j \bar{x}_j = \sum_i b_i \bar{y}_i$. This, together with weak duality, implies that \bar{x} and \bar{y} are optimal primal and dual solutions, respectively.

4. (3 + 7 = 10 points) Markov chains and LP duality

A Markov chain is a set of states (of a system) and the probability, for each pair of states, of transitioning from one state to the other. Markov chains have a wide range of applications including as models for several physical or biological processes, in economics and the social sciences, web search, and statistics.

Formally, a Markov chain is an $n \times n$ matrix P where p_{ij} denotes the probability of transitioning from state i to state j; if the system is in state i at time t, then the probability that it is in state j at time t + 1 is p_{ij} . Clearly, P satisfies the property that the sum of the entries along any row is 1.

One nice, and very useful, property of Markov chains is the existence of a stationary distribution π over the state space, where π is an $n \times 1$ vector with π_i being the probability of the system being in state i. We say that π is stationary if the following holds: if at any time t, π gives the probability distribution for the state of the given system, then π is also the probability distribution for the state in time t+1.

For any Markov chain matrix, the existence of a stationary distribution π can be shown easily using LP duality, as we establish in this exercise.

(a) Consider the following LP (over variables π_i) whose constraints define the stationary distribution.

$$\min \sum_{i} \pi_{i}$$

$$\left(\sum_{j} p_{ji} \pi_{j}\right) - \pi_{i} = 0 \quad \forall i$$

$$\sum_{j} \pi_{j} \geq 1$$

$$\pi_{i} > 0 \quad \forall i$$

Show that the above LP is feasible if and only if the Markov chain has a stationary distribution.

Answer: If the LP is feasible, there exists a nonnegative π such that $P\pi = \pi$. Since $\sum_j \pi_j \geq 1$, we can set $\pi' = \pi/(\sum_j \pi_j)$ to obtain a stationary distribution satisfying $P\pi' = \pi'$. If the Markov chain has a stationary distribution π^* then, $\pi_i = \pi_i^*$ is a feasible solution to the above LP.

(b) Derive the dual for the above LP. Analyze the dual and argue using duality that the primal is always feasible.

Answer: The dual for this LP is the following.

$$\sum_{i} p_{ij} v_i - v_j + \lambda \leq 1$$

$$\lambda \geq 0$$

We construct a feasible solution to the dual as follows. Set $v_i = 1$ for all i. For this solution, we get the first inequality of the dual to be $\lambda \leq 1$ since the sum of the entries in each column of P is 1. We set $\lambda = 1$ to obtain a feasible dual solution. It can also be shown that the dual is bounded; its value can be no more than 1 since the dual inequality corresponding to the smallest v_j will yield $\lambda \leq 1$ (using the fact that the sum of the entries in each column is 1). By weak duality, we have a primal optimal solution with $\sum_j \pi_j \leq 1$. But this implies that in the optimal solution $\sum_j \pi_j = 1$. And we obtain that $P\pi = \pi$.