

Graded Exercise 7

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Problem 1

a.

We have, the Primal problem can be represent in the matrix form as minimizing $w^T x$, subject to $Ax \geq b$. In the context of this problem:

- x is the variable vectors: $x = \begin{pmatrix} x_1 \\ x_2 \\ \dots \\ x_m \end{pmatrix}$
- w is the weight vector with dimension m : $w = \begin{pmatrix} w_1 \\ w_2 \\ \dots \\ w_m \end{pmatrix}$
- A is a $n \times m$ matrix, where every entry a_{ij} is 1 if the set S_j contains the element e_i , and zero otherwise: $A = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1m} \\ a_{21} & a_{22} & \dots & a_{2m} \\ \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & a_{nm} \end{pmatrix}$
- b is a $n \times 1$ vector, each entry of b is 1: $b = \begin{pmatrix} 1 \\ 1 \\ \dots \\ 1 \end{pmatrix}$

\Rightarrow The primal problem in matrix form is:

$$\begin{aligned} \min_x \quad & \begin{pmatrix} w_1 \\ w_2 \\ \dots \\ w_m \end{pmatrix}^T \begin{pmatrix} x_1 \\ x_2 \\ \dots \\ x_m \end{pmatrix} \\ \text{s.t} \quad & \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1m} \\ a_{21} & a_{22} & \dots & a_{2m} \\ \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & a_{nm} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \dots \\ x_m \end{pmatrix} \geq \begin{pmatrix} 1 \\ 1 \\ \dots \\ 1 \end{pmatrix} \end{aligned}$$

We can derive the dual: maximizing $b^T y$, subject to $A^T y \leq w$:

$$\begin{aligned} \max_y \quad & \begin{pmatrix} 1 \\ 1 \\ \dots \\ 1 \end{pmatrix}^T \begin{pmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{pmatrix} \\ \text{s.t} \quad & \begin{pmatrix} a_{11} & a_{21} & \dots & a_{m1} \\ a_{12} & a_{22} & \dots & a_{m2} \\ \dots & & & \\ a_{1n} & a_{2n} & \dots & a_{mn} \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{pmatrix} \leq \begin{pmatrix} w_1 \\ w_2 \\ \dots \\ w_m \end{pmatrix} \end{aligned}$$

We can express the matrix form to the sum form:

$$\begin{aligned} \max_y \quad & \sum_{i=1}^n y_i \\ \text{s.t} \quad & \sum_{i: e_i \in S_j} y_i \leq w_j, \quad j = 1, 2, \dots, m \end{aligned}$$

\Rightarrow The derived dual matches the given dual.

b.

We have:

$$c(I) = \sum_{j \in I} w_j$$

From the algorithm, set j is added if and only if $\sum_{i: e_i \in S_j} y_i = w_j$. Thus:

$$\begin{aligned} \sum_{j \in I} w_j &= \sum_{j \in I} \sum_{i: e_i \in S_j} y_i \\ &\leq \sum_{j=1}^m \sum_{i: e_i \in S_j} y_i \end{aligned}$$

Now, if we denote $f_i = |j : e_i \in S_j|$. By definition, $f = \max_i |f_i|$, we get that:

$$\begin{aligned} \sum_{j=1}^m \sum_{i: e_i \in S_j} y_i &= \sum_{i=1}^n f_i y_i \\ &\leq \sum_{i=1}^n f y_i = f \sum_{i=1}^n y_i \end{aligned}$$

$$\implies c(I) \leq f \sum_{i=1}^n y_i$$

C.

Consider for an arbitrary y_i . The given algorithm only increases y_i until the constraint is tight, and y start with the value 0. Thus y_i is always non negative. Also, for each i , y_i is increased once when e_i is checked, and stop immediately if the constraint is tight. So the dual constraint is preserved.

$\Rightarrow y_i$ is a feasible solution throughout the algorithm, and we can apply the weak duality theorem.

Let x^* be the optimal solution for the primal problem, and denote the optimal cost for the primal problem as OPT_{LP} . By the weak duality theorem, we have that:

$$OPT_{LP} = \sum_{j=1}^m w_j x_j^* \geq \sum_{i=1}^n b_i y_i = \sum_{i=1}^n y_i \quad (\text{Since } b_i = 1)$$

From the previous part, we have shown that:

$$\begin{aligned} c(I) &\leq f \sum_{i=1}^n y_i \\ &\leq f \sum_{j=1}^m w_j x_j^* = f \cdot OPT_{LP} \end{aligned}$$

Furthermore, the optimum cost of the integer problem is as most as good as the optimum cost for the relaxed problem, i.e., $OPT_{LP} \leq OPT$ (as in the lecture note)

$$\Rightarrow c(I) \leq f \cdot OPT_{LP} \leq f \cdot OPT$$

Problem 2

a.

Consider an arbitrary element $e_i \in U$, and denote $f_i = |j : e_i \in S_j|$. Thus by definition, $f = |\max_i f_i|$. Since x^* is the set of optimal solution for the primal problem, we have:

$$\sum_{j: e_i \in S_j} x_j^* \geq 1$$

In order for the above constraint to be valid, at least one of the x_j^* must have value at least $\frac{1}{f_i}$. Denote that set as x_i^* , we get:

$$x_i^* \geq \frac{1}{f_i} \geq \frac{1}{f} \quad (\text{since } f = |\max_i f_i|)$$

\Rightarrow For each element, there will be at least one set contains that element and have value at least $\frac{1}{f}$. And that set will be included into I .

\Rightarrow The algorithm returns a cover I .

b.

Consider an arbitrary set $x_j^* \in x^*$ that has value $1/f_j \geq 1/f$. So x_j^* will be rounded to 1 and added to I . This means that the value and thus the cost of adding x_j^* increased by a factor of $f_j \leq f$.

\Rightarrow Each chosen set will be increased in cost by at most a factor of f .

Consider also: in the worst case, all sets from the fractional solution will be chosen and increased in the cost by f times. Thus, $c(I)$ will be at most $f \cdot OPT_{LP}$, with OPT_{LP} denotes the optimal cost for the fractional problem. Also, $OPT_{LP} \leq OPT$ (As in the lecture note).

$$\Rightarrow c(I) \leq f \cdot OPT$$