LINFO2266 - Solutions

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1 Lagrangian Relaxation

1.1 Set Covering Problem

1. We introduce one Lagrangian multiplier for each constraint to obtain the Lagrangian relaxation:

$$\min \sum_{i=1}^{m} c_i x_i + \sum_{j=1}^{n} \lambda_j \left(1 - \sum_{\substack{i=1\\j \in S_i}}^{m} x_i \right)$$
 (1)

with $\lambda_j \geq 0, j \in \{1, \dots, n\}$. Note how we integrated the constraints: for any *feasible* solution of the original problem, we will have

$$1 - \sum_{\substack{i=1\\j \in S_i}}^{m} x_i \le 0 \tag{2}$$

which means a *negative* value will be added to the objective function and that we will thus obtain a *lower bound* on the optimal value of the problem.

For clarity, we rewrite eq. (1) as:

$$\min \sum_{i=1}^{m} \left(c_i - \sum_{j \in S_i} \lambda_j \right) x_i + \sum_{j=1}^{n} \lambda_j \tag{3}$$

For fixed values of the Lagrangian multipliers λ_j , we can obtain a lower bound by solving eq. (3). This problem is very simple to solve if we notice that:

- each x_i is multiplied by a fixed coefficient $\left(c_i \sum_{j \in S_i} \lambda_j\right)$
- the second term $\left(\sum_{j=1}^{n} \lambda_{j}\right)$ is constant

In order to minimize the objective function, it is sufficient to select the sets which have a negative coefficient:

$$x_i = \begin{cases} 1 & \text{if } c_i - \sum_{j \in S_i} \lambda_j \le 0\\ 0 & \text{otherwise.} \end{cases}$$
 (4)

- 2. By applying exactly what we described above, we get a lower bound value of 4.2.
- 3. We adapt the subgradient procedure covered in the lectures for this particular problem, and for multiple Lagrange multipliers in algorithm 1.

Algorithm 1 Subgradient procedure for the Set Covering Problem.

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1: \mathcal{L}^* \leftarrow -\infty, k \leftarrow 1, \mu_0 \leftarrow 1
  2: \lambda_{0,j} \leftarrow 0, 1 \le j \le n
  3: C^* \leftarrow a trivial solution, or none
  4: while \mu_k \geq \epsilon \ \mathbf{do}
             Compute cover C_k with weights \left(c_i - \sum_{j \in S_i} \lambda_{k,j}\right) for 1 \leq i \leq m
            \begin{array}{l} \mathcal{L}_{k} \leftarrow value\left(\mathcal{C}_{k}\right) + \sum_{j=1}^{n} \lambda_{k,j} \\ \text{if } \mathcal{L}_{k} > \mathcal{L}^{*} \text{ then} \\ \mathcal{L}^{*} \leftarrow \mathcal{L}_{k} \end{array}
  6:
  8:
  9:
             end if
             if C_k is feasible and value(C_k) < value(C^*) then
10:
                \mathcal{C}^* \leftarrow \mathcal{C}_k
11:
12:
             if \mathcal{L}^* = value(\mathcal{C}^*) then
13:
                   break
14:
            \lambda_{k+1,j} \leftarrow \max\left(0, \lambda_{k,j} + \mu_k \left(1 - \sum_{\substack{i=1\\j \in S_i}}^m x_i\right)\right) \text{ for } 1 \leq j \leq n
\mu_{k+1} \leftarrow \frac{1}{k} \text{ (or another valid update rule)}
k \leftarrow k+1
15:
16:
17:
18:
19: end while
20: return lb
```