

# LP formulation for regional-optimal bounds

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### Abstract

This technical report is written as a support material for the reader in [1], detailing the transformations to simplify an initial program to compute a tight bound for a  $\mathcal{C}$ -optimal assignment into a linear program (LP).

In this technical report we show how the initial program to compute a tight bound for a  $\mathcal{C}$ -optimal assignment, can be transformed into a linear program. Our departure point is the following program.

Find  $\mathcal{R}$ ,  $x^{\mathcal{C}}$  and  $x^*$  that  
minimize  $\frac{R(x^{\mathcal{C}})}{R(x^*)}$   
subject to  $x^{\mathcal{C}}$  being a  $\mathcal{C}$ -optimal for  $\mathcal{R}$

We start by analyzing what exactly means saying that  $x^{\mathcal{C}}$  is  $\mathcal{C}$ -optimal. The condition can be expressed as: for each  $x$  inside region  $\mathcal{C}$  of  $x^{\mathcal{C}}$  we have that  $R(x^{\mathcal{C}}) \geq R(x)$ . However, instead of considering all the assignments for which  $x^{\mathcal{C}}$  is guaranteed to be optimal, we consider only the subset of assignments such that the set of variables that deviate with respect to  $x^{\mathcal{C}}$  take the same value than in the optimal assignment. If we restrict to this subset of assignments, then each neighborhood covers a  $2^{|\mathcal{C}^{\alpha}|}$  assignments, one for each subset of variables in the neighborhood. Let  $2^{\mathcal{C}^{\alpha}}$  stand for the set of all subsets of the neighborhood  $\mathcal{C}^{\alpha}$ . Then for each  $A^k \in 2^{\mathcal{C}^{\alpha}}$  we can define an assignment  $x^{\alpha k}$  such that for every variable  $x_i$  in a relation completely covered by  $A^k$  we have that  $x_i^{\alpha k} = x_i^*$ , and

for every variable  $x_i$  that is not covered at all by  $A^k$  we have that  $x_i^{\alpha_k} = x_i^C$ . Then, we can write the value of  $x_i^{\alpha_k}$  as

$$R(x_k^\alpha) = \sum_{S \in T(A^k)} S(x_k^\alpha) + \sum_{S \in P(A^k)} S(x_k^\alpha) + \sum_{S \in N(A^k)} S(x_k^\alpha) \quad (1)$$

Now, the definition of  $\mathcal{C}$ -optimal can be expressed as  $A^k \in \{2^{C^{\alpha_k}} | C^{\alpha_k} \in \mathcal{C}\}$ :

$$R(x^C) \geq R(x_k^\alpha) = \sum_{S \in T(A^k)} S(x_k^\alpha) + \sum_{S \in P(A^k)} S(x_k^\alpha) + \sum_{S \in N(A^k)} S(x_k^\alpha) \quad (2)$$

that, by setting partially covered relations to the minimum possible reward (0 assuming non-negative rewards), results in:

$$R(x^C) \geq \sum_{S \in T(A^k)} S(x_k^\alpha) + \sum_{S \in N(A^k)} S(x_k^\alpha) \quad \forall A^k \in \{2^{C^{\alpha_k}} | C^{\alpha_k} \in \mathcal{C}\} \quad (3)$$

where  $T(A^k)$  is the set of completely covered relations,  $P(A^k)$  the set of partially covered relations and  $N(A^k)$  the set of relations not covered at all.

Given the definition of  $\mathcal{C}$ -optimality of equation 3, we can proceed on specifying the linear programming formulation of the initial problem. First, we assume that  $x_-^C = \langle 0, \dots, 0 \rangle$  and  $x^* = \langle 1, \dots, 1 \rangle$  where 0 and 1 stand for the first and second value in each variable domain. This assumption can be made without losing generality. Second, we create two real positive variables for each relation  $S \in \mathcal{R}$ , one representing  $S(x^C)$ , noted as  $x_S$ , and another one representing  $S(x^*)$ , noted as  $y_S$ .  $x^C$  in  $\mathcal{C}^\alpha$   $R(x^C) \geq R(x^\alpha)$  using a single equation, concretely the one that sets every variable in  $\mathcal{C}^\alpha$  to 1.

Third, to obtain the LP we can normalize the rewards of our optimal to add up to one ( $\sum_{S \in \mathcal{R}} y_S = 1$ ). This is a common procedure for turning a linear fractional program into a linear program.

Fourth, we add all the constraints from equation 3, to guarantee the optimality of  $x^C$ .

The linear program resulting from these is as follows:

$$\begin{aligned} & \text{minimize } \sum_{S \in \mathcal{R}} x_S \\ & \text{subject to} \\ & \quad \sum_{S \in \mathcal{R}} y_S = 1 \\ & \quad \text{and for each } A^k \in \{2^{C^{\alpha_k}} | C^{\alpha_k} \in \mathcal{C}\} \text{ also subject to} \\ & \quad \quad \sum_{S \in \mathcal{R}} x_S \geq \sum_{S \in T(A^k)} y_S + \sum_{S \in N(A^k)} x_S \end{aligned}$$

where

- $x$  is a vector of positive real numbers representing the values for each relation of the  $\mathcal{C}$ -optimal
- $y$  is a vector of real numbers representing the values for each relation of the optimal of the problem
- $T(A^k)$  contains the relations completely covered by  $A^k$ , and
- $N(A^k)$  contains the relations that are not covered by  $C^\alpha$  at all.

## References

- [1] M. Vinyals, E. Shieh, J. Cerquides, J. A. Rodriguez-Aguilar, Z. Yin, M. Tambe, and E. Bowring, *Quality guarantees for region optimal DCOP algorithms*, In: Proceedings of 10th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2011) (to appear).