

1. SDP Relaxation and Heuristics for Two-Way Partitioning Problem

(a) Q 5.39 textbook

$$\begin{aligned} \min \quad & x^T W x \\ \text{s.t.} \quad & x_i^2 = 1, \forall i \in \{1, \dots, n\} \end{aligned}$$

i. Show that the two-way partitioning problem can be cast as

$$\begin{aligned} \min \quad & \text{tr}(WX) \\ \text{s.t.} \quad & X \succeq 0, \text{rank}(X) = 1 \\ & X_{ii} = 1, \forall i \in \{1, \dots, n\} \end{aligned}$$

$$\begin{aligned} x^T W x &= \text{tr}(x^T W x) = \text{tr}(W x x^T) \\ \text{let } X &= x x^T \\ (\forall i) x_i^2 = 1 &\iff x_i \in \{-1, 1\} \implies x^T I x = n \\ x^T I x &= \text{tr}(x x^T) = n \\ (\forall i, j) X_{ij} &\in \{-1, 1\} \\ ((\exists i) X_{ii} = -1 &\implies \text{tr}(X) < n) \\ \text{thus, for } \text{tr}(X) &= n : (\forall i) X_{ii} = 1 \end{aligned}$$

$$\begin{aligned} X = x x^T &= x \begin{bmatrix} a_1 & a_2 & \dots & a_n \end{bmatrix} = \begin{bmatrix} a_1 x & a_2 x & \dots & a_n x \end{bmatrix}, a_i \in \mathbb{R}, x \in \mathbb{R}^n \\ (\forall i)(\exists j) \beta_{ij} a_i x &= a_j x \implies \beta_{ij} a_i x - a_j x = 0 \\ \text{let } \gamma_{ij} &= \beta_{ij} a_i - a_j \\ \gamma_{ij} x &= 0 \\ x \neq 0 &\implies ((\forall i)(\exists j) \gamma_{ij} = 0 \implies \text{linear dependence between all column vectors of } X) \\ \text{thus, } \text{rank}(X) &= 1 \end{aligned}$$

$$\begin{aligned} (\forall w) w^T X w &= w^T x x^T w = (x^T w)^T x^T w \\ (\forall i, w) (x^T w)_i (x^T w)_i &\geq 0 \implies (\forall w) (x^T w)^T (x^T w) \geq 0 \iff X \text{ is SPD} \end{aligned}$$

Combining all constraints and objective forms the desired result.

- ii. SDP relaxation of two-way partitioning problem. Using the formulation in part (a), we can form the relaxation:

$$\begin{aligned} \min \quad & \text{tr}(WX) \\ \text{s.t.} \quad & X \succeq 0 \\ & X_{ii} = 1, \forall i \in \{1, \dots, n\} \end{aligned}$$

This problem is an SDP, and therefore can be solved efficiently. Explain why its optimal value gives a lower bound on the optimal value of the two-way partitioning problem (5.113). What can you say if an optimal point X^* for this SDP has rank one?

$$\begin{aligned} L(X, Z, v) &= \text{tr}(WX) - \text{tr}(XZ) + \text{tr}(\text{diag}(v)\text{diag}(X) - I) \\ L(X, Z, v) &= -\text{tr}(\text{diag}(v)I) + \text{tr}(WX) - \text{tr}(XZ) + \text{tr}(\text{diag}(v)\text{diag}(X)) \\ g(Z, V) &= \begin{cases} -1^T v, & W - Z + \text{diag}(v) \succeq 0 \\ -\infty, & \text{o/w} \end{cases} \end{aligned}$$

dual problem :

$$\begin{aligned} \max_{Z, v} \quad & -1^T v \\ \text{s.t.} \quad & W - Z + \text{diag}(v) \succeq 0 \\ & Z \succeq 0 \end{aligned}$$

If an optimal point X^* for the relaxed problem has rank one:

X^* has minimal possible rank and $X^* \neq 0$, $X^* \succeq 0$.

$X^* \succeq 0$, so primal feasible.

Functions are all differentiable, KKT conditions apply at optimality where there exists a dual solution.

Dual of relaxed problem is feasible: $W + \text{diag}(v) \succeq Z, Z \succeq 0$

Using complementary slackness: $X^* \neq 0, -\text{tr}(X^*Z^*) = 0 \implies Z^* = 0$.

Dual problem of relaxed problem at optimality:

$$\begin{aligned} \max_{v, Z} \quad & -1^T v = [\max_v -1^T v]_{Z=Z^*} \\ \text{s.t.} \quad & W + \text{diag}(v) \succeq Z^*, Z^* = 0 \implies \\ \text{s.t.} \quad & W + \text{diag}(v) \succeq 0 \end{aligned}$$

This solution is equivalent to the solution of the dual of the original problem. Thus, if $\text{rank}(X^*) = 1$ of the relaxed problem, X^* obtains the same solution as the original problem where $x^*x^{*T} = X^*$ as required.

- iii. We now have two SDPs that give a lower bound on the optimal value of the two-way partitioning problem (5.113): the SDP relaxation (5.115) found in part (b), and the Lagrange dual of the two-way partitioning problem, given in (5.114). What is the relation between the two SDPs? What can you say about the lower bounds found by them? Hint: Relate the two SDPs via duality.

$$\begin{aligned}
 (5.115) \quad & \min \operatorname{tr}(WX) \\
 & s.t. \ X \succeq 0 \\
 & \quad X_{ii} = 1, \forall i \in \{1, \dots, n\}
 \end{aligned}$$

$$\begin{aligned}
 (5.114) \quad & \text{maximize } -1^T v \\
 & s.t. \ W + \operatorname{diag}(v) \succeq 0
 \end{aligned}$$

Taken from previous section, dual of relaxed problem:

$$\begin{aligned}
 L(X, Z, v) &= \operatorname{tr}(WX) - \operatorname{tr}(XZ) + \operatorname{tr}(\operatorname{diag}(v)\operatorname{diag}(X)) - I \\
 L(X, Z, v) &= -\operatorname{tr}(\operatorname{diag}(v)I) + \operatorname{tr}(WX) - \operatorname{tr}(XZ) + \operatorname{tr}(\operatorname{diag}(v)\operatorname{diag}(X)) \\
 g(Z, V) &= \begin{cases} -1^T v, & W - Z + \operatorname{diag}(v) \succeq 0 \\ -\infty, & \text{o/w} \end{cases}
 \end{aligned}$$

Dual problem:

$$\begin{aligned}
 & \max_{Z, v} -1^T v \\
 & s.t. \ W - Z + \operatorname{diag}(v) \succeq 0 \\
 & \quad Z \succeq 0
 \end{aligned}$$

It is evident that solution to the dual of relaxed problem has a tightened generalized inequality constraint due to Z compared to (5.114):

$$W + \operatorname{diag}(v) \succeq Z$$

This leads to potentially bigger v and hence potentially larger objective value of dual maximization problem (smaller objective value to the primal minimization problem). Thus, solution of relaxed problem provides a lower bound to the the original problem.

(b) Q 11.23(b-d) textbook

- b) heuristic partitioning
- c) randomized method
- d) greedy heuristic refinement

2. Interior Point Method