Exercise session notes - Week 12

Formulations as SDP + Schur Complement

Consider a quadratic program of the form

$$\min \quad c^{\top} x$$
$$x^{\top} Q x + b^{\top} x + d \le 0$$

If Q is positive semi-definite, then this problem is convex and we can solve it efficiently via Newton Descent. But what if Q has negative eigenvalues? Then the problem is no longer convex, but we can still solve it partially with a relaxation to a SDP. We first define the matrix $X = xx^{\top}$ which is a symmetric matrix and contains x_ix_j on the *i*th row and *j*th column. This is often used when we have a quadratic form because then

$$x^{\top}Qx = \sum_{i,j} x_i Q_{ij} x_j = \sum_{i,j} X_{ij} Q_{ij} = \text{Tr}(XQ) = \langle X, Q \rangle$$

and this is an affine function on S^n_+ . Therefore our QP is equivalent to

$$\min \quad c^{\top} x$$
$$\langle X, Q \rangle + b^{\top} x + d \le 0$$
$$X = xx^{\top}$$

Finally we can relax the last constraint and we get the SDP

$$\min_{\substack{c \in X, Q \\ X \neq 0}} c^{\top} x$$

$$c^{\top} x$$

$$c^{\top} x$$

$$c^{\top} x$$

$$d \leq 0$$

$$X \geq 0$$

Note that by solving this problem we obtain a lower bound on the optimal value of the QP.

A very important fact on positive semi-definite matrices is the Schur Complement:

Proposition (Schur Complement). Let X be a symmetric block matrix

$$X = \begin{pmatrix} A & B \\ B^{\top} & C \end{pmatrix}$$

If $A \succ 0$ then

$$X\succeq 0\iff C-B^{\top}A^{-1}B\succeq 0$$

If $C \succ 0$ then

$$X \succeq 0 \iff A - BC^{-1}B^{\top} \succeq 0$$

Consider the following 0-1 QP

$$\label{eq:state_equation} \begin{aligned} \max \quad y^\top B y \\ y \in \{0,1\}^n \end{aligned}$$

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We define as before $Y = yy^{\top}$ and note that

$$y_i^2 = y_i \implies \operatorname{diag}(Y) = y$$

In particular we can write

$$Y = \operatorname{diag}(Y)\operatorname{diag}(Y)^{\top}$$

We can relax this constraint into the following

$$Y - \operatorname{diag}(Y)\operatorname{diag}(Y)^{\top} \succeq 0$$

and by the Schur Complement we can write a relaxation of the QP program as the SDP

$$\max_{X} \langle Y, B \rangle$$

$$\begin{pmatrix} Y & \operatorname{diag}(Y) \\ \operatorname{diag}(Y)^{\top} & 1 \end{pmatrix} \succeq 0$$

$$Y \succeq 0$$

As before, by solving this problem we obtain a lower bound on the optimal value of the 0-1 QP.

Another application of the Schur Complement comes from geometry: We are given k points $z_1, \ldots, z_k \in \mathbb{R}^n$ and we want to find an Ellipse E that contains all the points and has minimal volume. We can describe an Ellipse as

$$E_{P,c} = \{ x \mid (x-c)^{\top} P(x-c) \}$$

where $c \in \mathbb{R}^n$ is the center of the Ellipse and $P \succ 0$ is the matrix that gives us the stretch of the Ellipse (if P = I then we obtain a circle). Moreover the volume of the Ellipse is proportional to

$$\operatorname{vol}(E_{P,c}) \sim \sqrt{\det(P^{-1})}$$

Therefore we can model this problem as the following abstract program

$$\min_{P,c} \quad \text{vol}(E_{P,c}) \sim \sqrt{\det(P^{-1})}$$
s.t.
$$z_i \in E_{P,c} \quad \forall i$$

Since the function $\log(\cdot)$ is monotone, we can apply that to the objective function and the problem remains the same.

$$\min_{P,c} \quad \log\left(\sqrt{\det(P^{-1})}\right) = -\frac{1}{2}\log\det(P)$$

s.t. $(z_i - c)^{\top}P(z_i - c) \le 1 \quad \forall i$

Recall that $\log \det(\cdot)$ is a concave function. Since $P \succ 0$ we can write it as $P = B^{\top}B$ and we get

$$\min_{B,c} -\frac{1}{2} \log \det(B^{\top}B) = -\log \det(B)$$
s.t. $1 - (z_i - c)^{\top}B^{\top}B(z_i - c) > 0 \quad \forall i$

Finally, we can define d := Bc and apply the Schur Complement to the constraint so that obtain the SDP

$$\min_{B,d} - \log \det(B)$$
s.t.
$$\begin{pmatrix} I & Bz_i - d \\ (Bz_i - d)^\top & 1 \end{pmatrix} \succeq 0 \quad \forall i$$

After we have solved this program we can obtain a solution to the original problem by computing $P = B^{\top}B$ and $c = B^{-1}d$.