

ADVANCED ALGORITHM DESIGN

Homework 2

October 27, 2024

Problem 1

Solution

Problem 2

The maximum cut problem asks us to cluster the nodes of a graph $G = (V, E)$ into two disjoint sets X, Y so as to maximize the number of edges between these sets:

$$\max_{X, Y} \sum_{(i, j) \in E} \mathbf{1}[(i \in X, j \notin X) \vee (i \in Y, j \notin Y)].$$

Consider instead clustering the nodes into three disjoint sets X, Y, Z . Our goal is to maximize the number of edges between different sets:

$$\max_{X, Y, Z} \sum_{(i, j) \in E} \mathbf{1}[(i \in X, j \notin X) \vee (i \in Y, j \notin Y) \vee (i \in Z, j \notin Z)].$$

Design an algorithm based on SDP relaxation that solves this problem with approximation ratio greater than 0.7.

Solution

(We assume undirected graph G just to write the notation $\{i, j\}$) For the problem with two partitions, we had modeled the problem with having variables $x_v \in \{\pm 1\}$ for each vertex $v \in V$. For the corresponding problem with three partitions we will restrict each such variable to be a 2-vector among $\mathbf{a}_1 := (1, 0), \mathbf{a}_2 := \left(-\frac{1}{2}, \frac{\sqrt{3}}{2}\right), \mathbf{a}_3 := \left(-\frac{1}{2}, -\frac{\sqrt{3}}{2}\right)$. It is easy to verify that $\mathbf{a}_1^\top \mathbf{a}_2 = \mathbf{a}_2^\top \mathbf{a}_3 = \mathbf{a}_3^\top \mathbf{a}_1 = -\frac{1}{2}$. The three vertices $\mathbf{a}_{1,2,3}$ stand for the three partitions X, Y, Z . Any edge $(u, v) \in E$ that gets assigned different classes of vertices, say $\mathbf{x}_u = \mathbf{a}_1, \mathbf{x}_v = \mathbf{a}_2$, contributes exactly $1 = \frac{2}{3}(1 - \mathbf{a}_1^\top \mathbf{a}_2)$ to the cut value. If they are in the same class then $\mathbf{x}_u = \mathbf{x}_v$ and $\mathbf{x}_u^\top \mathbf{x}_v = 1$ giving a contribution of 0 from the expression $\frac{2}{3}(1 - \mathbf{x}_u^\top \mathbf{x}_v)$.

Let's make things formal now. Let $G = (V = [n], E)$ be the given graph. Introduce variables $\mathbf{x}_v \in \mathbb{R}^2$, one for each $v \in V$, and constrain them $\mathbf{x}_v \in \{\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3\}$ where \mathbf{a}_i are as in the above paragraph. Given the above discussion, our problem is modeled as follows

$$\begin{aligned} f^* := \max_{\mathbf{x}_1, \dots, \mathbf{x}_n \in \mathbb{R}^2} & \quad \frac{2}{3} \sum_{(i, j) \in E} (1 - \mathbf{x}_i^\top \mathbf{x}_j) \\ \text{s.t.} & \quad \mathbf{x}_i \in \{\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3\} \quad \forall i \in V \end{aligned} \tag{1}$$

We are essentially interested in $\min_{\mathbf{x}_1, \dots, \mathbf{x}_n \in \mathbb{R}^2} \frac{2}{3} \sum_{(i, j) \in E} \mathbf{x}_i^\top \mathbf{x}_j$ s.t. $\mathbf{x}_i \in \{\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3\} \quad \forall i \in V$.

To get an SDP relaxation, we relax our constraints to $\|\mathbf{x}_i\|_2 = 1 \quad \forall i \in V$ and $\mathbf{x}_i^\top \mathbf{x}_j \geq -\frac{1}{2}$. The last constraint gives the best angle separation among 3 vectors on \mathbb{S}^2 in the

following sense: if $t \in \mathbb{R}$ is such that $\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3 \in \mathbb{S}^2$ satisfy $\mathbf{v}_i^\top \mathbf{v}_j \leq t$ ($\forall i \neq j$) then $0 \leq \|\mathbf{v}_1 + \mathbf{v}_2 + \mathbf{v}_3\|_2^2 = 3 + 2 \cdot 3 \cdot t \implies t \geq -1/2$. So we design an SDP with the rank-2

matrix $\begin{bmatrix} \mathbf{x}_1^\top \\ \vdots \\ \mathbf{x}_n^\top \end{bmatrix}_{n \times 2} [\mathbf{x}_1 \ \cdots \ \mathbf{x}_n]_{2 \times n} \succeq 0$ in mind:

$$\begin{aligned} \frac{2m}{3} - f_S &= \min_{X \in S^{n \times n}} \text{Tr} \left[\frac{2}{3} Q X \right] \\ \text{s.t.} \quad &X_{ii} = 1 \ \forall i \in V \\ &X_{ij} \geq -\frac{1}{2} \ \forall i \neq j \in V \\ &X \succeq 0 \end{aligned} \tag{2}$$

where Q is a matrix whose $(i, j)^{\text{th}}$ entry is 1 if $\{i, j\} \in E$ and 0 otherwise, $S^{n \times n}$ denotes the space of all real symmetric $n \times n$ matrices, and f_S is the optimal value obtained from SDP relaxation.

Let's say the optimal solution of this SDP is attained at X^* , take a Cholesky factorization $X^* = V^\top V$ where $V \in \mathbb{R}^{r \times n}$ and $r = \text{rank } V$. Let the columns of V be $\mathbf{y}_1, \dots, \mathbf{y}_n \in \mathbb{R}^r$. In the rounding step, we choose random vectors $\mathbf{R}_1, \mathbf{R}_2, \mathbf{R}_3 \in \mathbb{R}^r$ such that each $\mathbf{R}_{i,j} \sim \mathcal{N}(0, 1)$ (for $1 \leq j \leq r$) is chosen independently. These will give us the partitions, by rounding each \mathbf{y}_i to the component nearest among \mathbf{R}_j . More precisely, we partition $V = V_1 \sqcup V_2 \sqcup V_3$ as follows:

$$\begin{aligned} V_1 &:= \{i \in V \mid \mathbf{y}_i^\top \mathbf{R}_1 \geq \mathbf{y}_i^\top \mathbf{R}_2, \mathbf{y}_i^\top \mathbf{R}_1 \geq \mathbf{y}_i^\top \mathbf{R}_3\} \\ V_2 &:= \{i \in V \mid \mathbf{y}_i^\top \mathbf{R}_2 \geq \mathbf{y}_i^\top \mathbf{R}_1, \mathbf{y}_i^\top \mathbf{R}_2 \geq \mathbf{y}_i^\top \mathbf{R}_3\} \\ V_3 &:= \{i \in V \mid \mathbf{y}_i^\top \mathbf{R}_3 \geq \mathbf{y}_i^\top \mathbf{R}_2, \mathbf{y}_i^\top \mathbf{R}_3 \geq \mathbf{y}_i^\top \mathbf{R}_1\} \end{aligned}$$

while breaking ties at random. In fact assign $\mathbf{x}_i := \mathbf{a}_j$ if $i \in V_j$.

Let f_R denote the cut value produced by the above-mentioned randomized rounding. So $f_R = \sum_{\{i,j\} \in E} \mathbf{1}[\mathbf{x}_i \neq \mathbf{x}_j]$. We are interested in $\mathbb{E}[f_R] = \sum_{\{i,j\} \in E} \mathbb{P}[\mathbf{x}_i \neq \mathbf{x}_j]$.

Problem 3

The Ellipsoid algorithm we saw in the lecture solves convex programs assuming a separation oracle. Here, we want to show the opposite. To be more specific, consider the following two tasks regarding a convex body \mathcal{K} :

- OPTIMIZE(\mathcal{K}) : given a vector $c \in \mathbb{R}^n$, output $\arg \max_{x \in \mathcal{K}} c^\top x$;
- SEPARATE(\mathcal{K}) : given a point $x \in \mathbb{R}^n$, output either $x \in \mathcal{K}$ or a separating hyperplane.

We are going to show that if for a specific convex body \mathcal{K} , there is a polynomial time algorithm for OPTIMIZE(\mathcal{K}), then there is a polynomial time algorithm for SEPARATE(\mathcal{K}).

- (a) Suppose for a given x , we can solve the following LP with infinitely many constraints (finding the optimal w and T). Show that we can use such an algorithm to solve SEPARATE(\mathcal{K}).

$$\begin{aligned} \max_{w \in \mathbb{R}^n, T \in \mathbb{R}} \quad & w^\top x - T \\ \text{s.t.} \quad & w^\top y \leq T \quad \forall y \in \mathcal{K} \\ & -1 \leq T \leq 1 \end{aligned} \tag{3}$$

- (b) Design a polynomial time separation oracle for the above LP using OPTIMIZE(\mathcal{K}), and conclude.

Solution

- (a) Suppose the value of this LP is > 0 and is attained at (\bar{w}, \bar{T}) . Then for any $y \in \mathcal{K}$, $\bar{w}^\top y - \bar{T} \leq 0$. This means that $x \notin \mathcal{K}$.

Suppose $x \notin \mathcal{K}$. Then there is a vector $w \in \mathbb{R}^n$ such that $w^\top x > 0$ and $w^\top y \leq 0 \quad \forall y \in \mathcal{K}$. This $(w, T = 0)$ is feasible to 3 with objective > 0 . Thus its optimal value is > 0 .

Therefore $x \in \mathcal{K}$ iff the optimal value of 3 is ≤ 0 . If ≤ 0 with optimal $w = \bar{w}$, a separating hyperplane is \bar{w} because of what is discussed above.

- (b)

Problem 4

Describe separation oracles for the following convex sets. Your oracles should run in linear time, assuming that the given oracles run in linear time (so you can make a constant number of black-box calls to the given oracles).

Solution

Problem 5

Solution

Problem 6

Solution