

# Maximum Cut

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## **Abstract**

TODO

# 1 Introduction

## 2 Mathematical Formulations

### 3 Relaxations for Max Cut

#### 3.1 Eigenvalue Relaxation

**Proposition 1.** *The optimal value of  $z^*$  in the maxcut problem defined on graph  $G = (V, E)$  satisfies*

$$z^* \leq z^{ev} := \frac{n}{4} \lambda_{\max}(L(G))$$

*Proof.* From the previous section we saw that

$$z^* = \frac{1}{4} \max_{\mathbf{z} \in \{-1, 1\}} \sum_{i \in V} \sum_{j \in V} w_{ij} (1 - z_i z_j) \quad (1)$$

Since  $z_i \in \{-1, 1\}$  it is clear that  $z_i z_i = 1$ . Then, we can express (1) as

$$\frac{1}{4} \max_{\mathbf{z} \in \{-1, 1\}} \sum_{i \in V} \sum_{j \in V} w_{ij} (z_i z_i - z_i z_j) \quad (2)$$

Rearranging these terms we see that

$$\frac{1}{4} \max_{\mathbf{z} \in \{-1, 1\}} \sum_{i \in V} z_i \left( \sum_{j \in V} w_{ij} \right) z_i - \sum_{i \in V} z_i \sum_{j \in V} w_{ij} z_j \quad (3)$$

Recall that  $D(G)_{ii} = \sum_{j \in V} w_{ij}$  and  $D(G)_{ij} = 0$  for  $i, j \in V$ . The first term in (3) can be expressed as  $\mathbf{z}^\top D(G) \mathbf{z}$ . Likewise, the weighted adjacency matrix  $A(G)_{ii} = 0$  and  $A(G)_{ij} = w_{ij}$  for  $i, j \in V$ . The second term can be expressed as  $\mathbf{z}^\top A(G) \mathbf{z}$  and now

$$\frac{1}{4} \max_{\mathbf{z} \in \{-1, 1\}} \mathbf{z}^\top D(G) \mathbf{z} - \mathbf{z}^\top A(G) \mathbf{z} \quad (4)$$

Since the matrix product is distributive we have

$$\frac{1}{4} \max_{\mathbf{z} \in \{-1, 1\}} \mathbf{z}^\top (D(G) - A(G)) \mathbf{z} \quad (5)$$

By definition of the Laplacian of  $G$  we have that the optimal solution of maxcut can be computed as

$$\frac{1}{4} \max \{ \mathbf{z}^\top L(G) \mathbf{z} \mid \mathbf{z} \in \{-1, 1\} \} \quad (6)$$

Taking the continuous relaxation of (6), namely  $z \in [-1, 1]$ , is equivalent to maximizing over the  $\|\mathbf{z}\|_\infty = 1$ . We can relax this further by maximizing over a ball of radius  $\sqrt{n}$ . In other words, our region is now defined where  $\|\mathbf{z}\| \leq \sqrt{n}$ .

$$z^* \leq \frac{1}{4} \max \{ \mathbf{z}^\top L(G) \mathbf{z} \mid \mathbf{z} \leq \sqrt{n} \} \quad (7)$$

We can define our problem over the unit ball with a simple transformation. Let  $\|\mathbf{z}\| = \sqrt{n}\mathbf{y}$  and we now have

$$z^* \leq \frac{n}{4} \max\{\mathbf{y}^\top L(G) \mathbf{y} \mid \|\mathbf{y}\| \leq 1\} \quad (8)$$

Since for any symmetric matrix  $\mathbf{A}$ ,  $\max\{\mathbf{x}^\top \mathbf{A} \mathbf{x} \mid \|\mathbf{x}\| \leq 1\} = \lambda_{\max}(\mathbf{A})$  and  $L(G)$  is symmetric, then we have

$$z^* \leq z^{ev} := \frac{n}{4} \lambda_{\max}(L(G)) \quad (9)$$

□

**Proposition 2.** *The optimal value of  $z^*$  in the maxcut problem defined on graph  $G = (V, E)$  satisfies*

$$z^* \leq z^{ev} := -\frac{1}{4} \sum_{i=1}^n u_i + \frac{n}{4} \lambda_{\max}(L(G) + \text{diag}(\mathbf{u}))$$

for all  $\mathbf{u} \in \mathbb{R}^n$

*Proof.* Consider the maximization problem

$$\max\{\mathbf{z}^\top (L(G) + \text{diag}(\mathbf{u})) \mathbf{z} \mid \mathbf{z} \in \{-1, 1\}^n\}$$

Note that no matter the value of  $\mathbf{u} \in \mathbb{R}^n$ ,  $L(G) + \text{diag}(\mathbf{u})$  remains to be a symmetric square matrix. As a result,

$$\lambda_{\max}(L(G) + \text{diag}(\mathbf{u})) = \max\{\mathbf{z}^\top (L(G) + \text{diag}(\mathbf{u})) \mathbf{z} \mid \mathbf{z} \in \{-1, 1\}^n\}$$

Using the distributive property of the matrix product we can separate this into two separate maximization problems

$$\max\{\mathbf{z}^\top L(G) \mathbf{z} \mid \mathbf{z} \in \{-1, 1\}^n\} + \max\{\mathbf{z}^\top \text{diag}(\mathbf{u}) \mathbf{z} \mid \mathbf{z} \in \{-1, 1\}^n\}$$

Expanding this further yields the optimization problem

$$\max_{\mathbf{z} \in \{-1, 1\}^n} \sum_{i=1}^n \sum_{j=1}^n w_{ij} (1 - z_i z_j) + \sum_{i=1}^n u_i \quad (10)$$

Which is closely related to the objective function in our previous formulation. We can obtain a relationship between (10) and  $z^*$ :

$$z^* = \frac{1}{4} \max\{\mathbf{z}^\top (L(G) + \text{diag}(\mathbf{u})) \mathbf{z} \mid \mathbf{z} \in \{-1, 1\}^n\} - \frac{1}{4} \sum_{i=1}^n u_i$$

We repeat the process from the previous proof of relaxing the variables so that they are continuous and then further relaxing this problem onto a ball of radius  $\sqrt{n}$ .

$$z^* \leq \frac{1}{4} \max\{\mathbf{z}^\top (L(G) + \text{diag}(\mathbf{u})) \mathbf{z} \mid \|\mathbf{z}\| \leq \sqrt{n}\} - \frac{1}{4} \sum_{i=1}^n u_i$$

Let  $\mathbf{z} = \sqrt{n}\mathbf{x}$ .

$$z^* \leq \frac{n}{4} \max\{\mathbf{x}^\top (L(G) + \text{diag}(\mathbf{u}))\mathbf{x} \mid \|\mathbf{x}\| \leq 1\} - \frac{1}{4} \sum_{i=1}^n u_i$$

Finally, we obtain the inequality

$$z^* \leq z^{ev}(\mathbf{u}) = - \sum_{i=1}^n u_i + \frac{n}{4} \lambda_{\max}(L(G) + \text{diag}(\mathbf{u})) \quad (11)$$

□