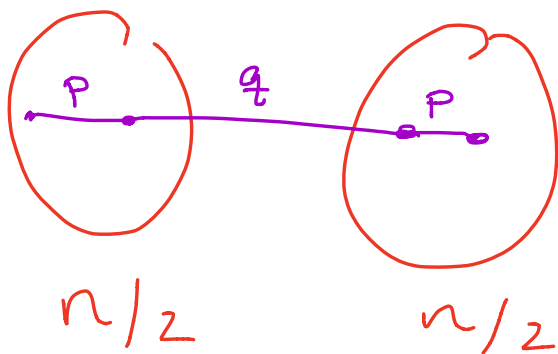


SBM



Goal: What are conditions on (p, z) that allow exact recovery of (s, \bar{s})

$$p = \frac{\alpha \log n}{n} \quad z = \beta \frac{\log n}{n}$$

Q: $\min_{\alpha, \beta} |\alpha - \beta| \geq f$ s.t. we

get exact recovery?

$\frac{1}{\sqrt{2}} \begin{pmatrix} 1 & i \\ -1 & i \end{pmatrix}$

Thrm: $1 - \sqrt{p} > \epsilon$ exact recovery.

Thrm: When $\sqrt{2} - \sqrt{p} > \epsilon$, then the exact solution is recovered by an SDP. whp.

$$\max A \cdot X, \quad X_{ii} = 1, \quad X \succeq 0$$

Rmk: This is the relaxation of

$$\max x^T A x \quad x_i \in \{-1, 1\}$$

- max cut problem.

Roadmap: Construct a dual solution whp.

Let $g = \frac{1}{\sqrt{2}}(1_s - 1_{\bar{s}})$

$X = g g^T$ is feasible solution.

n...1 cond

dual SDP

$$\min \sum z_i$$

$$\text{diag}(z) \preceq A$$

$$z \in \mathbb{R}^n$$

Solve using
complementary
slackness.

We will give a dual solution

z such that

$$(i) \ z \text{ feasible \& } z - A \succeq 0$$

$$(ii) \ (z - A) \cdot gg^T = 0$$

$$(iii) \ \lambda_2(z - A) \succeq 0$$

Rmk: (z, gg^T)

primal
sol

dual
sol.

Way to check if optimal

$$\begin{aligned}\text{val}(gg^T) &= A \cdot gg^T \stackrel{\text{d.f.}}{\leq} \text{diag}(z) \cdot gg^T \\ &= \sum_{i=1}^n z_i (gg^T)_{ii} \stackrel{\text{p.f.}}{=} \sum z_i \\ &= \text{val}(z)\end{aligned}$$

So only equal when

$$A \cdot gg^T \stackrel{\text{d.f.}}{=} \text{diag}(z) \cdot gg^T$$

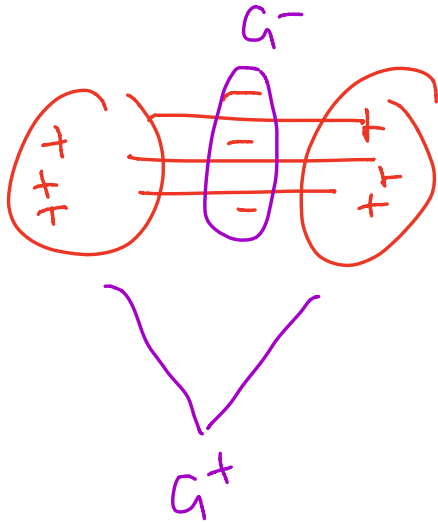
So when weak duality is tight
we get optimality.

So

(ii) $\Rightarrow (z, gg^T)$ optimal

(iii) \Rightarrow uniqueness of optimal.

Finding \mathbb{Z}



$$\min (D_+ - A_+) \cdot X - (D_- + A_-) \cdot X$$

$$= \min \left[(D_+ - D_-) - \underbrace{A_+ - A_-}_A \right] \cdot X \quad L_{sbm}$$

$$I \cdot X = 1$$

$$L_{sbm} = [(D_+ - D_-) - A]$$

$$X^T L_{sbm} = \sum_{i,j \in G_+} (x_i - x_j)^2$$

$$-\sum_{i,j \in G_-} (x_i + x_j)^2$$

$$(i) \quad g^T L_{SBM} g = 0$$

$$(\text{goal: } Z - A = L_{SBM})$$

Expected Behavior L_{SBM}

$$x_{ij}^- = e_i - e_j$$

$$x_{ij}^+ = e_i + e_j$$

$$L_{SBM} = \sum_{G_+} x_{ij}^- x_{ij}^{-T} - \sum_{G_-} x_{ij}^+ x_{ij}^{+T}$$

$$\mathbb{E}[L_{SBM}] = \sum_S p x_y x_y^{-T} +$$

$$\begin{aligned}
 & \sum_{\bar{S}} p x_j^- x_j^{-T} \\
 & - \sum_{\substack{i \in S \\ j \in \bar{S}}} \varepsilon x_{ij}^+ x_{ij}^{+T}
 \end{aligned}$$

$$= p L(K_S) + p L(K_{\bar{S}})$$

$$- \varepsilon \left[\begin{array}{c|c} \begin{matrix} n/2 & \dots & n/2 \\ \hline 1 & \dots & n/2 \end{matrix} & \begin{matrix} 1 \\ \hline \dots & n/2 \end{matrix} \end{array} \right]$$

S
 \bar{S}

$$= p L(K_S) + p L(K_{\bar{S}}) - nI + L(K_{S, \bar{S}})$$

$$= p L(K_U) + (p - \varepsilon) L(K_{S, \bar{S}})$$

$$= \varepsilon L(K_U) + \varepsilon \mathbf{1} \mathbf{1}^T - \varepsilon n I$$

$$= \varepsilon L(K_U) + \varepsilon \mathbf{1} \mathbf{1}^T - \varepsilon n I$$

$$L(K_{S,\bar{S}}) = \frac{L(K_U) + gg^T}{2}$$

So

$$\mathbb{E}[L_{SBM}] = \frac{3}{2} (p-q) L(K_U) + (p-q) \frac{gg^T}{2} - q \mathbb{1}^T$$