

Assignment 5:

1 - Hidden Partition Problem:

1.1 - Re-Formulating the optimization problem -

$$1) \quad x_i = \begin{cases} 1 & \text{if } i \in S_1 \\ -1 & \text{if } i \in S_2. \end{cases}$$

we know that  $(S_1^*, S_2^*) = \underset{|S_1|=|S_2|}{\operatorname{argmax}} A_{ij}$  i, j same partition.

$$x_i x_j = \begin{cases} 1 & \text{if both } i \text{ and } j \text{ are in same partition.} \\ -1 & \text{otherwise.} \end{cases}$$

$$(S_1^*, S_2^*) = \underset{|S_1|=|S_2|}{\operatorname{argmax}} \sum_{\substack{i, j \\ \text{same partition}}} A_{ij}$$

$$= \underset{|S_1|=|S_2|}{\operatorname{argmax}} \sum_{x_i, x_j \in S_1} A_{ij} (x_i x_j)^{+1} + \sum_{x_i, x_j \in S_2} A_{ij} (x_i x_j)^{+1} + \sum_{\substack{(x_i, x_j) \\ \neq \text{part.}}} A_{ij} (x_i x_j)^{-1}$$

$$= \underset{|S_1|=|S_2|}{\operatorname{argmax}} \sum_{x_i, x_j \in S_1} A_{ij} + \sum_{x_i, x_j \in S_2} A_{ij} \rightarrow \sum_{\substack{(x_i, x_j) \\ \neq \text{part.}}} A_{ij}$$

so obtain  $1 + x_i x_j$ :

$$1 + x_i x_j = \begin{cases} 2 & \text{if same partition.} \\ 0 & \text{otherwise} \end{cases}$$

$$= \underset{\substack{x_i, x_j \\ \in S_1}}{\operatorname{argmax}} \frac{1}{2} \sum A_{ij} (1 + x_i x_j) + \frac{1}{2} \sum_{\substack{x_i, x_j \\ \in S_2}} A_{ij} (1 + x_i x_j) - \frac{1}{2} \sum_{\substack{(x_i, x_j) \\ \neq \text{part.}}} A_{ij} (1 + x_i x_j)$$

b/c  $0 \text{ if } x_i, x_j \neq \text{part.} \Rightarrow 0$

$$= \underset{x}{\operatorname{argmax}} \sum A_{ij} (1 + x_i x_j).$$

SOLO



By saying  $|S_1| = |S_2|$ ,  $\Rightarrow$  nb of  $x_i = 1$  = nb of  $x_i = -1$ .

$$\Rightarrow \operatorname{argmax}_x \sum_{i,j} A_{ij} (1 + x_i x_j) \quad \text{s.t.} \quad \begin{cases} \sum_{i=1}^n x_i = 0 \\ x_i \in \{-1, +1\} \end{cases}$$

2) changes:

$$\operatorname{argmax}_x x^T A x - \lambda \left( \sum_i x_i \right)^2 \quad \text{s.t.} \quad x_i \in \{-1, +1\}.$$

$$\begin{aligned} x^T A x - \lambda \left( \sum_i x_i \right)^2 &= x^T A x - \lambda x^T \mathbf{1} \mathbf{1}^T x \\ &= \operatorname{Tr}(A x x^T) - \lambda \operatorname{Tr}(\mathbf{1} \mathbf{1}^T x x^T) \\ &= -\langle x, \tilde{A} \rangle. \end{aligned}$$

Show:

$$\operatorname{argmin}_x \langle x, \tilde{A} \rangle \quad \text{s.t.} \quad x \geq 0, \operatorname{rank}(x) \leq 1, x_{ii} = 1$$

our problem is now to:

$$\operatorname{argmax}_x -\langle x, \tilde{A} \rangle \equiv \min_x \langle x, \tilde{A} \rangle$$

$$X = X X^T, \tilde{A} = \lambda \mathbf{1} \mathbf{1}^T - A.$$

$$X X^T = \begin{pmatrix} 1 & & \\ & \ddots & \\ & & 1 \end{pmatrix}$$

at most one eigenvalue positive

$$\begin{pmatrix} 1 & & \\ & \ddots & \\ & & 1 \end{pmatrix}$$

$$\mathbf{1} \mathbf{1}^T$$

$$= \mathbf{1} \mathbf{1}^T = 1 \text{ bcz } x_i + x_i$$

the values of  $x$  are all = 1

$\Rightarrow$  at most one eigenvalue  $\geq 0 \Rightarrow \operatorname{rank}(x) \leq 1$ .

can write our prob:

$$\operatorname{argmin}_x \langle x, \tilde{A} \rangle \quad \text{s.t.} \quad \operatorname{rank}(x) \leq 1; x \geq 0, x_{ii} = 1.$$

3)

$$\min_{X, Z} \langle X, \tilde{A} \rangle \quad \text{s.t.} \quad X \geq 0; Z_{ii} = 1; Z = X.$$

ADMM algorithm: let's see how the algo works.

$$\min f_1(x_1) + f_2(x_2) + \dots + f_m(x_m) \quad \text{s.t.} \quad A_1 x_1 + A_2 x_2 + \dots + A_m x_m = b.$$

$$\mathcal{L}_p(x_1, \dots, x_m, \lambda) = \sum_{i=1}^m f_i(x_i) + \lambda^T \left( \sum_{i=1}^m A_i x_i - b \right) + \rho \left\| \sum_{i=1}^m A_i x_i - b \right\|^2.$$

fixing one variable.

$$\Rightarrow \begin{cases} x_i^{k+1} = \operatorname{argmin}_{x_i} \mathcal{L}_p(x_i, x_2^{k+1}, \dots, x_i, x_{i+1}^k, \dots, x_m^k; \lambda^k). \\ \lambda^{k+1} = \lambda^k + \rho \left( \sum_{i=1}^m A_i x_i^{k+1} - b \right). \end{cases}$$

our opt. prob  $\operatorname{argmin}_x \langle x, \tilde{A} \rangle \quad \text{s.t.} \quad \operatorname{rank}(x) \leq 1; x \geq 0, x_{ii} = 1.$

we can write it as a summ. over all  $x$ .

$$\min_{X, Z} \sum_i \langle X_i, \tilde{A} \rangle. \text{ For } Z = X, \text{ ADMM will select "i" from } X \text{ with others fixed (in } Z), \text{ and min:}$$

SOLO



$$\min L = \sum_i \langle x_i, \tilde{A} \rangle + \langle \lambda, \sum_i x_i - \tilde{z} \rangle + \rho \|\sum_i x_i - \tilde{z}\|^2.$$

$$\Rightarrow \min_{x, \tilde{z}} \langle x, \tilde{A} \rangle \text{ s.t.: } x \geq 0; \tilde{z} \leq 1, \tilde{z} = x.$$

#### 4) ADMM Update Rules:

$$x^{k+1} = \operatorname{argmin}_x L(x, \tilde{z}^k, \lambda^k)$$

$$\tilde{z}^{k+1} = \operatorname{argmin}_{\tilde{z}} L(\tilde{x}^{k+1}, \tilde{z}, \lambda^k).$$

$$\lambda^{k+1} = \lambda^k + \rho (\tilde{x}^{k+1} - \tilde{z}^{k+1}).$$

#### 1.2: Min Max Problem:

$$\min_x \max_y x^T A y. \quad \nabla f = \begin{pmatrix} \frac{\partial f}{\partial x} = Ay \\ \frac{\partial f}{\partial y} = x^T A \end{pmatrix}$$

Has many applications such as GANS --

Please Refer to the PDF file for this part. (MATLAB Code).

#### EG Method: (Extra Gradient):

Update Rule:

$$x^{k+1/2} = x^k - \alpha \nabla f(x^k, y^k)$$

$$y^{k+1/2} = y^k + \alpha \nabla f_y(x^k, y^k).$$

then:

$$\begin{aligned} x^{k+1} &= x^k - \alpha \nabla f_x(x^{k+1/2}, y^{k+1/2}) \\ y^{k+1} &= y^k + \alpha \nabla f_y(x^{k+1/2}, y^{k+1/2}). \end{aligned}$$

Gradient computed above.

#### OGDA (Optimistic Gradient Descent Ascent).

$$x^{k+1} = x^k - \alpha \nabla f_x(x^k, y^k) - \alpha (\nabla f_x(x^k) f(x^{k-1}, y^{k-1})).$$

$$y^{k+1} = y^k + \alpha \nabla f_y(x^k, y^k) - \alpha (\nabla f_y(y^k) f(x^k, y^{k-1})).$$

$$\Rightarrow x^{k+1} = x^k - 2\alpha Ay^k + \alpha Ay^{k-1}$$

$$y^{k+1} = y^k + 2\alpha A^T x^k - \alpha A^T x^{k-1}.$$

check Matlab code.

SOLO



PP method:

need to find  $x^{k+1}$  &  $y^{k+1}$  s.t.:  $(x^{k+1}, y^{k+1})$

$$x^{k+1} = x^k - \alpha \nabla_x f(x^{k+1}, y^{k+1}).$$

$$y^{k+1} = y^k - \alpha \nabla_y f(x^{k+1}, y^{k+1}).$$

$$\nabla_x f = Ay \rightarrow x^{k+1} = x - \alpha Ay^{k+1}.$$

$$\nabla_y f = x^T A \rightarrow y^{k+1} = y - \alpha x^{k+1 T} A.$$

$$\Rightarrow x^{k+1} = x^k - \alpha (y^k - \alpha x^{k+1 T} A) A$$

$$= x^k - \alpha Ay^k - \alpha A \alpha x^{k+1 T} A$$

$$= x^k - \alpha Ay^k - \alpha^2 A x^{k+1 T} A.$$

$$= x^{k+1} + \alpha^2 A x^{k+1 T} A = x^k - \alpha Ay^k$$

$$x^{k+1} (I + \alpha^2 A A^T) = x^k - \alpha Ay^k$$

$$x^{k+1} = (x^k - \alpha Ay^k) (I + \alpha^2 A A^T)^{-1}.$$

check Matlab code.

For other qns, please check the MATLAB codes with their interpretation on PDF.