

* Method of Multipliers (Augmented Lagrangian)

$$\min -\frac{1}{2}(x_1^2 + x_2^2)$$

$$\text{s.t. } x_1 + 2x_2 = 3$$

Nice regularization of optimization

$$L_c(x, \nu) = -\frac{1}{2}(x_1^2 + x_2^2) + \nu(x_1 + 2x_2 - 3) + \frac{c}{2}(x_1 + 2x_2 - 3)^2, \quad c \geq 1$$

landscape \rightarrow can convert non-convex problems to potentially SC problems.

At iteration k:

$$\left. \begin{aligned} x_k &= \arg \min L_{c_k}(x, \nu_k) \\ \nu_{k+1} &= \nu_k + c_k h(x_k) \\ c_{k+1} &= \beta c_k, \quad \beta > 1 \end{aligned} \right\}$$

* Dual-ascent:

$$\min f(x)$$

$$\text{s.t. } Ax = b$$

At iteration k:

$$x_k = \arg \min_x f(x) + \nu^T Ax$$

$$\nabla g(\nu_k) = Ax_k - b$$

$$\nu_{k+1} = \nu_k + \alpha_k \nabla g(\nu_k)$$

residual

* Dual Decomposition:

$$\min_{x_i \in \mathbb{R}^{n_i}} \sum_{i=1}^B f_i(x_i)$$

$$\text{s.t. } Ax = b$$

$$A = [A_1 \ A_2 \ \dots \ A_B]$$

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_B \end{bmatrix}$$

(Broadcast)

Scatter-Gather

$$\rightarrow x_i^{(k)} = \arg \min f_i(x) + \nu_k^T A_i x \quad \forall i$$

$$\nu_{k+1} = \nu_k + \alpha_k \left(\sum_{i=1}^B A_i x_i^{(k)} - b \right)$$

Parallelizability

$$\left. \begin{array}{l} \min f(x) \\ \text{s.t. } Ax=b \end{array} \right\} \begin{array}{l} \text{Dual ascent} \\ \text{with} \\ \text{"augmented Lagrangian"} \end{array}$$

$$L_c(x, v) = \underbrace{f(x) + v^T(Ax-b)} + \frac{c}{2} \|Ax-b\|^2$$

* Can we enjoy the best of both worlds? \longrightarrow Yes

Augment Lagrangian's
optimization landscape

Parallelizable
(Dual-ascent)

ADMM (Alternating direction method of Multipliers)

* Consider the problem of the form:

$$\min_{x, z} f(x) + g(z)$$

$$\text{s.t. } Ax + Bz = c$$

$$\underline{L_p(x, z, v)} = \underline{f(x) + g(z) + v^T(Ax + Bz - c)} + \frac{\rho}{2} \|Ax + Bz - c\|^2$$

At iteration k: (Using Method of Multipliers)

$$\left. \begin{array}{l} (x_k, z_k) = \arg \min_{(x, z)} L_p(x, z, v_k) \\ v_{k+1} = v_k + \rho (Ax_k + Bz_k - c) \end{array} \right\}$$

ADMM repeats the step: $(x^{(k-1)}, z^{(k-1)}, v_k)$

$$\begin{array}{l} \underline{x}^{(k)} = \arg \min_x L_p(x, z^{(k-1)}, v_k) \\ \underline{z}^{(k)} = \arg \min_z L_p(x^{(k)}, z, v_k) \\ \Rightarrow \underline{v}_{k+1} = v_k + \rho (Ax^{(k)} + Bz^{(k)} - c) \end{array}$$

* Convergence guarantees:

Under modest assumptions on f, g (do not require A, B to be full rank),

then ADMM iterates satisfy for any $\underline{\rho} > 0$,

↳ Residual convergence:

$$r^{(k)} = Ax^{(k)} + Bz^{(k)} - c \rightarrow 0 \text{ as } k \rightarrow \infty$$

↳ Objective convergence:

$$f(x^{(k)}) + g(z^{(k)}) \rightarrow f^* + g^* \text{ as } k \rightarrow \infty$$

↳ Dual convergence:

$$v^{(k)} \rightarrow v^* \text{ as } k \rightarrow \infty$$

* Scaled-form ADMM: $w := v/\rho$

$$\begin{aligned} \underline{L}_\rho(x, z, v) &= f(x) + g(z) + v^T(Ax + Bz - c) + \frac{\rho}{2} \|Ax + Bz - c\|^2 \\ &= f(x) + g(z) + 2\rho \cdot \left(\frac{v}{2\rho}\right)^T (Ax + Bz - c) + \frac{\rho}{2} \|Ax + Bz - c\|^2 \\ &= f(x) + g(z) + 2 \cdot \rho \cdot \frac{w^T}{2} (Ax + Bz - c) + \frac{\rho}{2} \|Ax + Bz - c\|^2 \\ &\quad + \frac{\rho}{2} \|w\|^2 - \frac{\rho}{2} \|w\|^2 \\ &= f(x) + g(z) + \frac{\rho}{2} \left[\|w\|^2 + \|Ax + Bz - c\|^2 + 2w^T(Ax + Bz - c) \right] - \frac{\rho}{2} \|w\|^2 \\ &= f(x) + g(z) + \frac{\rho}{2} \|Ax + Bz - c + w\|^2 - \frac{\rho}{2} \|w\|^2 \end{aligned}$$

Final step is:

$$w_{k+1} = w_k + r^{(k)}$$

$$w_{k+1} = w_0 + \text{Sum of residuals.}$$

— x — x — x — x — x — x — x —

* Basics of Graph Theory:

convex / SC / PL-inequality

$$\min_{x \in \mathbb{R}^n} f(x)$$

$$\min_{\substack{x_1, \dots, x_N \\ \in \mathbb{R}^{n_1} \times \dots \times \mathbb{R}^{n_N}}} \sum_{i=1}^N f_i(x_i)$$

— s.t. $x_1 = x_2 = \dots = x_N$

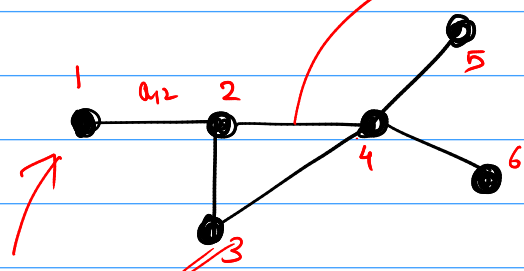
x^*

$$\sum_{i=1}^n f_i(x)$$

x^*

f_i 's are private objective functions.

$$f_i := \sum_{(u,v) \in E_i} l(\hat{y}_i, y_i)$$



Undirected, unweighted graph

nodes/
vertices/
agents

$$2 \in N_1$$

N_i : neighborhood set of agent i

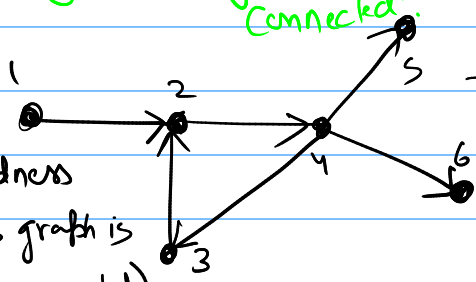
$$a_{ij} = \begin{cases} 1 & \text{if } \exists \text{ an edge b/w } i \text{ and } j \\ 0, & \text{else} \end{cases}$$

$$N_2 = \{1, 3, 4\}$$

V : set of vertices
 $\{1, 2, 3, 4, 5, 6\}$

E : set of edges.

Is this graph connected?

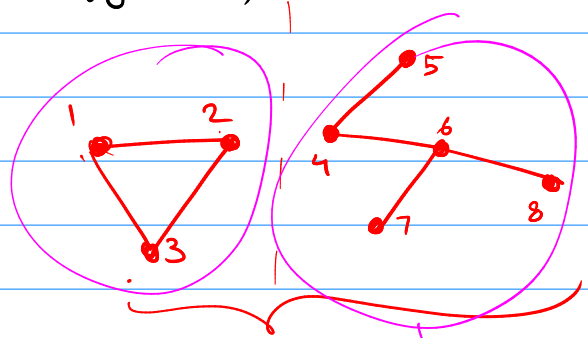


Directed graphs (Digraphs)

Directed, weighted graphs

Strongly connectedness
(this graph is not strongly connected)

*

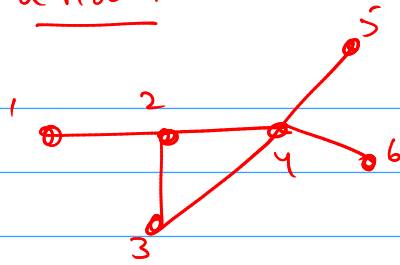


Graph is not connected:

Connected: A graph is connected if there exists a path b/w any pair of nodes.

Subgraphs → Connected components of a graph.

* Degree of a node:



$d_i :=$ size of the neighbourhood set N_i

$$d(1) = 1$$

$$d(2) = 3$$

$$d(3) = 2$$

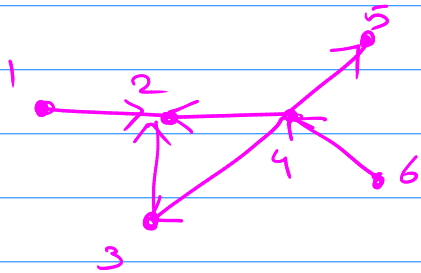
$$d(4) = 4$$

$$d(5) = 1$$

$$d(6) = 1$$

Degree matrix of a graph:

$$D = \begin{bmatrix} 1 & & & & & \\ & 3 & & & & \\ & & 2 & & & \\ & & & 4 & & \\ & & & & 1 & \\ & & & & & 1 \end{bmatrix}$$



In-degree

$$d_{in}(1) = 0$$

$$d_{out}(1) = 1$$

* Edge Adjacency matrix:

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

For each i , $\sum_{j=1}^N a_{ij} = d_i \leftarrow$ degree of node i

* Laplacian: $L := D - A$ } symmetric

$$L_{ij} = d_{ij} - a_{ij} \quad \sum_{j=1}^N l_{ij} = \sum_{j=1}^N d_{ij} - \sum_{j=1}^N a_{ij} = 0$$

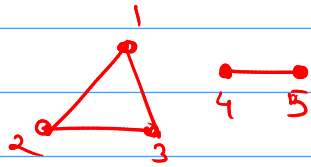
$$L \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = 0$$

$\rightarrow 0$ is an eigenvalue of L with $\mathbb{1}_N$ being the corresponding eigenvector.

Normalized Laplacian $\left\{ \begin{array}{l} L_{sym} = I - D^{-1/2} A D^{-1/2} \\ L_{rw} = I - D^{-1} A \end{array} \right\}$ \rightarrow n Cut

Spectral Clustering \leftarrow $\left\{ \begin{array}{l} L_{sym} \\ L_{rw} \end{array} \right\}$ \rightarrow Ratio Cut

$L \mathbb{1} = 0 \rightarrow$ Is 0 a simple eigenvalue?

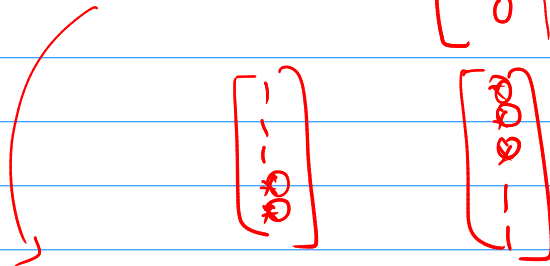


Disconnected graph
connected components is 2.

$$A = \left[\begin{array}{c|c} A_1 & 0 \\ \hline 0 & A_2 \end{array} \right]$$

$$D = \begin{bmatrix} 2 & & & & \\ & 2 & & & \\ & & 2 & & \\ & & & 1 & \\ & & & & 1 \end{bmatrix}$$

$$L = D - A = \left[\begin{array}{c|c} L_1 & 0 \\ \hline 0 & L_2 \end{array} \right]$$



Algebraic multiplicity of 0 eigenvalues of L
= # of connected components.

Eigenvalues of Laplacian:

$$0 = \lambda_1 < \lambda_2 \leq \lambda_3 \leq \dots$$

Smallest non-zero eigenvalue

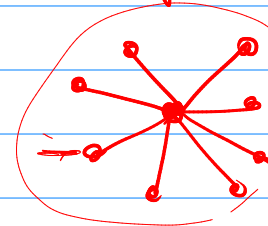
$\lambda_2(L) \rightarrow$ Fiedler eigenvalue.

Ex: Line graph:



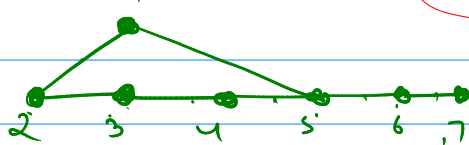
diameter = $N-1$

Ex: star graph:



diameter = 2

Diameter of a graph:



$1 \rightarrow 2 = 1 \leftarrow$ diameter = 4

$1 \rightarrow 3 = 2$

Brendan McKay Fiedler value $\geq \frac{4}{n(\text{diameter})}$ } for connected graphs

* L is a positive semi-definite matrix $\Rightarrow \lambda(L) \geq 0$.

$$\begin{aligned} & x^T L x \geq 0 \\ &= \sum_{i=1}^N \sum_{j=1}^N x_i l_{ij} x_j \\ &= \sum_{i=1}^N \sum_{j=1}^N x_i (D_{ij} - A_{ij}) x_j \\ &= \sum_{i,j=1}^N x_i D_{ij} x_j - \sum_{i,j=1}^N x_i A_{ij} x_j \\ &= \sum_{i=1}^N x_i^2 d_i - \sum_{i,j=1}^N x_i x_j A_{ij} \\ &= \frac{1}{2} \sum_{i=1}^N x_i^2 d_i + \frac{1}{2} \sum_{j=1}^N x_j^2 d_j - \sum_{i,j=1}^N x_i x_j A_{ij} \\ &= \frac{1}{2} \sum_{i,j=1}^N A_{ij} (x_i - x_j)^2 \geq 0 \end{aligned}$$