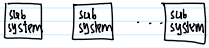




Page 1: * Distributed Convex optimization:

- Convex problem
- ↓ partition into coupled subsystems



- divide variables, constraints, objective terms in two groups: **local** Variables, constraints, objective terms appearing in only one subsystem.

complicating

n n n n n n more than one subsystem

- describe by hypergraph
- Subsystems are nodes
- complicating (variables, constraints, objective terms) are hyperedges

Complicating stuff (बाधा चीज):
जो जगल चीजो स्टफ. ओकरे fix करल all the subsystems become separable.

Page 2: Conditional Separability:

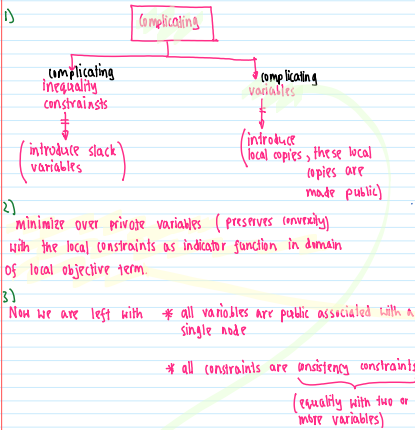
• Separable problem:

$$\begin{aligned} \min_x \left(\begin{array}{l} \forall f_1(x_1) + f_2(x_2) \\ x_1 \in C_1, x_2 \in C_2 \end{array} \right) &= \min_x \left(\begin{array}{l} f_1(x_1) + I_{C_1}(x_1) + f_2(x_2) + I_{C_2}(x_2) \\ \end{array} \right) \quad \# \text{Separable problem} \\ &= \left(\min_{x_1} f_1(x_1) + I_{C_1}(x_1) \right) + \left(\min_{x_2} f_2(x_2) + I_{C_2}(x_2) \right) \\ &= \left(\min_{x_1} f_1(x_1) \right) + \left(\min_{x_2} f_2(x_2) \right) \\ &\quad \left(\begin{array}{l} x_1 \in C_1 \\ x_2 \in C_2 \end{array} \right) \end{aligned}$$

- Conditionally separable: Two subsystems: conditionally separable \Leftrightarrow separable when the complicating variables are fixed
- \Leftrightarrow any two subsystems are not connected by an edge.

Example:
 $\min_{z_1, z_2, x} f_1(z_1, x) + f_2(z_2, x)$
 z_1, z_2, x
 x : complicating variable, public or interface or boundary variable between the two subproblems
 z_1, z_2 : local variables
 • hypergraph: two nodes connected by an edge

Page 3: Transformation to standard form:



- 1) minimize over private variables (preserves convexity) with the local constraints as indicator function in domain of local objective term.
- 2) Now we are left with:
 - * all variables are public associated with a single node
 - * all constraints are consistency constraints (equality with two or more variables)

Example:

$$\begin{aligned} \min_{z_1, z_2, x} \left(\begin{array}{l} \forall f_1(z_1, x) + f_2(z_2, x) \\ x_1 = x_2 \end{array} \right) &= \min_{z_1, z_2, x_1, x_2} \left(\begin{array}{l} \forall f_1(z_1, x_1) + f_2(z_2, x_2) \\ x_1 = x_2 \end{array} \right) \quad \# \text{eliminate local variables} \\ &\quad \# \text{by minimizing over private variables } z_1, z_2 \\ &= \min_{x_1, x_2} \left(\begin{array}{l} \forall f_1(z_1, x_1) + f_2(z_2, x_2) \\ x_1 = x_2 \end{array} \right) \\ &= \min_{x_1, x_2} \left(\begin{array}{l} \forall f_1(z_1) + f_2(z_2) \\ x_1 = x_2 \end{array} \right) \quad \# \text{consistency constraint} \\ &\quad \# \text{in hypergraph general form} \end{aligned}$$

- Page 4:
- General form:
 - n subsystems with x_1, \dots, x_n (each of them are vectors)
 - m nets with common variable values z_1, \dots, z_m
 - Problem structure:

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

these matrices give the netlist

Problem structure

$$\begin{aligned} & \text{Minimize } \sum_{i=1}^n s_i(x_i) \\ & \text{subject to } V_{i \in \{1, \dots, m\}} x_i = E_i z \end{aligned}$$

these matrices give the netlist

$E_i z = \begin{bmatrix} \bar{r}_1^T z \\ \vdots \\ \bar{r}_m^T z \end{bmatrix}$ where $\bar{r}_j = e_j = (0, \dots, \underbrace{1}_{j \text{th place}}, \dots, 0)$ if x_{ij} is in net j .

see the circuit example below.

y_i : associated dual variable

*** Optimality conditions (KKT)**

$$\begin{aligned} & \left(\begin{aligned} & \text{Minimize } \sum_{i=1}^n s_i(x_i) \\ & \text{subject to } V_{i \in \{1, \dots, m\}} x_i = E_i z \end{aligned} \right) : \text{primal problem} \\ & \text{--- } y_i : \text{dual variable} \end{aligned}$$

$$\begin{aligned} L(x_1, \dots, x_n, z, y_1, \dots, y_m) &= \sum_{i=1}^n s_i(x_i) + \sum_{i=1}^m y_i^T (x_i - E_i z) \\ &= \sum_{i=1}^n (s_i(x_i) - y_i^T x_i) - \sum_{i=1}^m y_i^T (E_i z) \\ & \quad \left(\begin{matrix} E_1^T y_1 \\ \vdots \\ E_m^T y_m \end{matrix} \right)^T z \end{aligned}$$

KKT condition:

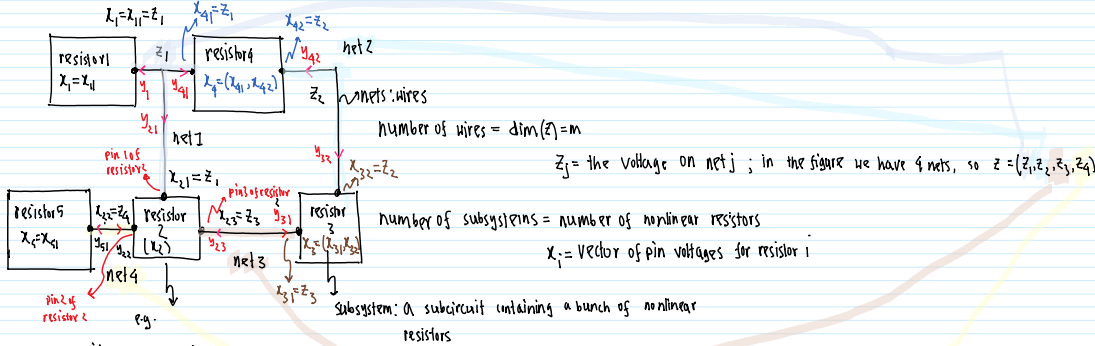
Vanishing gradient of the Lagrangian:

$$\begin{aligned} \nabla_{(x_1, \dots, x_n, z)} L(x_1, \dots, x_n, z, y_1, \dots, y_m) &= \begin{bmatrix} \nabla_{x_1} s_1 - y_1 \\ \vdots \\ \nabla_{x_n} s_n - y_m \\ \nabla_z L \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix} \\ \Leftrightarrow \nabla_{x_i} s_i(x_i) - y_i = 0 & \text{# } z \text{ equation shows the relation that is true for every subsystem} \\ \nabla_z L = 0 & \Leftrightarrow \sum_{i=1}^m E_i^T y_i = 0 \text{ # Shows the condition of the dual variables} \\ & \quad \text{# dual variables on each net sum to zero} \\ \nabla_z \left(\sum_{i=1}^m (E_i^T y_i)^T z \right) & \\ = \sum_{i=1}^m \nabla_z \left[(E_i^T y_i)^T z \right] & \text{# } \nabla_z \text{ linear operator} \\ = \sum_{i=1}^m (E_i^T y_i) & \text{# sum } z \text{ terms to zero offset} \\ & \quad \text{# } \nabla_z \text{ linear operator} \\ & \quad \text{# sum } z \text{ terms to zero offset} \\ & \quad \text{# } \nabla_z \text{ linear operator} \\ & \quad \text{# sum } z \text{ terms to zero offset} \end{aligned}$$

Primal feasibility:

$x_i = E_i z$ # Primal variables on each net # are the same

*** Let's talk about circuit interpretation: Look at an example.**



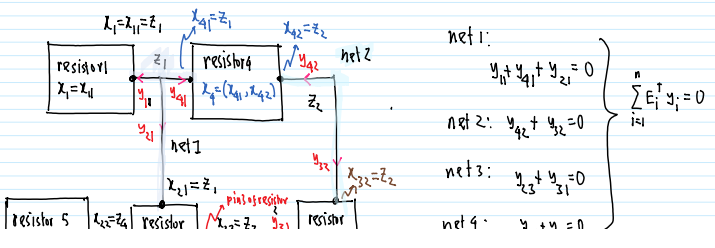
$$x_2 = \begin{bmatrix} x_{21} \\ x_{22} \\ x_{23} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \end{bmatrix} = \begin{bmatrix} e_1^T \\ e_2^T \\ e_3^T \end{bmatrix} z = E_2 z$$

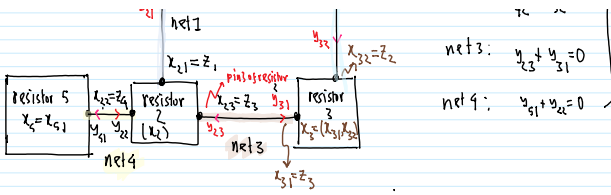
as pin 1 voltage of resistor 2 (x_{21}) is in net 1, the first row of E_2 is e_1^T
" " " " " " " x_{22} " " " " 2nd " " " " e_2^T
" " " " " " " x_{23} " " " " 3rd " " " " e_3^T

Page 4: # interpretation of the dual variables y : Vector of current entering resistor i

so the current vector going in the pins of resistor 2, $y_2 = \begin{bmatrix} y_{21} \\ y_{22} \\ y_{23} \end{bmatrix}$

*** What would be KCL then?**
Sum of currents leaving net j is zero in fact this is the optimality condition: $\sum_{i=1}^m E_i^T y_i = 0$





* V-I characteristic of the resistor

$$y_i = \nabla f_i(x_i)$$

$$\downarrow$$

$$\begin{bmatrix} y_{i1} \\ \vdots \\ y_{in_i} \end{bmatrix} = \begin{bmatrix} \frac{\partial}{\partial x_{i1}} f_i(x_i) \\ \vdots \\ \frac{\partial}{\partial x_{in_i}} f_i(x_i) \end{bmatrix}$$

$f_i(x_i)$: cost function of the resistor i
 # cost function of the i th resistor

* So we have in the circuit interpretation:

x_i = vector of voltages on the pins of nonlinear resistor i $|_{i=1}^n$
 $z = (z_1, \dots, z_m)$ = vector of voltages on the wires (nets) of the circuit
 y_i = vector of currents going in different pins of the nonlinear resistor

The circuit equations are:

- KVL: $\sum_{i \in \mathcal{E}_j} x_i = E_j z_j \rightarrow$ primal feasibility originally
- KCL: $\sum_{i=1}^n E_i^T y_i = 0 \rightarrow$ optimality condition on the dual variables
- V-I characteristic of the resistor: $\sum_{i \in \mathcal{E}_i} y_i = \nabla f_i(x_i) \rightarrow$ optimality condition for the subsystems

So, circuit equations are the same as the optimality conditions !!!

Ⓢ Convexity of f_i is the incremental passivity of resistor i
 $(x_i - \tilde{x}_i)^T (y_i - \tilde{y}_i) \geq 0, y_i = \nabla f_i(x_i), \tilde{y}_i = \nabla f_i(\tilde{x}_i)$ # explanation needed later...

Decomposition methods:

- Solve distributed problems iteratively
- algorithm state maintained in nets
- Each step:
 - parallel update of subsystem primal and dual variables, based on adjacent net states (local blocks optimization)
 - update of the net states, based on adjacent subsystems (central block update)
- Algorithms differ in 1) interface to subsystems
 2) state and update

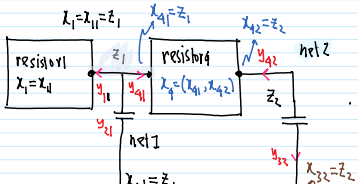
Primal Decomposition:

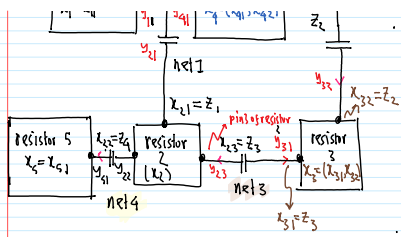
repeat:

- Distribute net variables to adjacent subsystems
 $x_i := E_i z$ # primal feasibility is always maintained
 # dual optimal condition is approached in limit.
- Optimize subsystems separately
 solve subsystems to evaluate $y_i = \nabla f_i(x_i)$ # Each of these subsystems are voltage controlled
 # voltage x_i vector is asserted to different pins of resistor i
 # current through the pins are then determined
- Collect and sum dual variables for each net.
 $u := \sum_{i=1}^n E_i^T y_i$ # this u corresponds to dual residual at
 # optimal solution u is 0
- update net variables
 $z := z - M_R u$ # State of the algorithm is the netvoltage vector z
 (chosen by standard gradient or subgradient rules)

Circuit interpretation:

- connect capacitor to each net, system relaxes to equilibrium
- forward Euler update is primal decomposition
- incremental passivity implies convergence to equilibrium





*Needs more clarifications