

Consensus Optimization

6:36 PM

Consensus Optimizat...

Consensus using Monotone Operator Splitting

Consensus Optimization:

Compare this with
[\[Consensus using Proximal ADMM\]](#)

$$\left(\begin{array}{l} \text{Consensus using Proximal ADMM} \\ \left(\begin{array}{l} \sum_{i=1}^n f_i(x_i) = f(x) \\ x_1 = x_2 = \dots = x_n \end{array} \right) \end{array} \right) = \left(\begin{array}{l} \sum_{i=1}^n f_i(x_i) + l_C(x) : f \in \{(x_1, \dots, x_n) | x_1 = \dots = x_n\} \\ \# \text{ Consensus Optimization Problem} \end{array} \right)$$

the minimizer x^* is $\arg \min_{x \in X} \left(\sum_{i=1}^n f_i(x_i) \right) + \varphi_c(x)$

thm: proximal operator is the resolvent of subdifferential operator

- the resolvent of a subdifferential operator w.r.t function ψ is the proximal map, i.e.

$$R_{\lambda y}(\Theta) = (1 + \lambda y)^{-1} \Theta = \text{prox}_{\lambda y}(\Theta) = \underset{\Theta}{\operatorname{argmin}} \left(\lambda y(\Theta) + \frac{1}{2} \|\Theta - \Theta^*\|_F^2 \right) = \underset{\Theta}{\operatorname{argmin}} \left(y(\Theta) + \frac{1}{2\lambda} \|\Theta - \Theta^*\|_F^2 \right)$$

$$\# \text{ by definition } \text{prox}_{\frac{\lambda}{2}}(\mathbf{y}) = \underset{\mathbf{x}}{\operatorname{arg\,min}} \left(\varphi(\mathbf{x}) + \frac{1}{2} \|\mathbf{y} - \mathbf{x}\|_2^2 \right)$$

- $$R_{N_i}(x) = \Pi_i(x) \quad \text{• resolution of the normal cone operator of the normal}$$

So, to solve $B(x) + A(x) \geq 0$ we apply D-R splitting as follows: [\[# eq: Douglas-Rachford splitting \(Ernest's notation\)\]](#)

$$1) \quad x^{k+1} = R_\beta(z^k) = R_{\frac{\beta}{\lambda f}}(z^k) = \text{prox}_{\frac{\beta}{\lambda f}}(z^k) = \underset{y}{\operatorname{argmin}} \left(f(y) + \frac{1}{2\lambda} \|y - z^k\|_2^2 \right)$$

$$V f(y) + \frac{1}{\lambda} \|y - z_i\|_2^2 = V \left(\sum_{i=1}^n \left(f_i(y_i) + \frac{1}{\lambda} \|y_i - z_i\|_2^2 \right) \right) = \sum_{i=1}^n V(f_i(y_i) + \frac{1}{\lambda} \|y_i - z_i\|_2^2)$$

$\sum_{i=1}^n f_i(y_i)$ $\sum_{i=1}^n \|y_i - z_i\|_2^2$

note that this is
separable so each part can be

so up can split

Note that this is separable so each part can be solved independently.

so we can split the iterate x^{k+1} into n separate local iterates,

$$\underset{\substack{i \in \{1, \dots, n\} \\ j}}{\underset{\text{argmin}}{x_i^{k+1}}} = \underset{y_i}{\left(S_i(y_i) + \frac{1}{\lambda} \| y_i - z_i^k \|_2^2 \right)}$$

Each of them are local iteration

$$\text{2) } \frac{x^{k+1}}{z} = x^k \frac{1}{z} - z^k = \begin{pmatrix} x_1 & x_2 & \dots & x_n \\ \vdots & & & \\ x_n & x_{n-1} & \dots & x_1 \end{pmatrix} \leftrightarrow \bigvee_{i \in \{1, \dots, n\}} \frac{x^{k+1}}{z_i} = x_i^{k+1} - z_i^k$$

$$3) \quad x^{k+1} = R_A(\tilde{x}^{k+\frac{1}{2}}) = R_{\alpha_i}(\tilde{x}^{k+\frac{1}{2}}) = \Pi_r(\tilde{x}^{k+\frac{1}{2}})$$

Now we want to find the projection on the consensus set: $C = \{x \mid x_1 = x_2 = \dots = x_n\}$

$$\prod_{i=1}^n x_i = \left[\begin{array}{c} \bar{x} \\ \vdots \\ \vdots \\ \bar{x} \end{array} \right] \text{ Where } \bar{x} = \frac{1}{n} \sum_{i=1}^n x_i; \quad \text{# Though this is intuitive, I need to figure out a proof later}$$

$\prod_i (\tilde{z}^{k+1}) = \left(\frac{1}{n} \sum_{i=1}^n z_i^{k+1} \right)^n$ so we can split this one to as well, and localize in $\# n$ blocks. note that this is a vector

$$\forall i \in \{1, \dots, n\} \quad x_i^{k+1} = \frac{1}{n} \sum_{j=1}^n z_j^{k+1/2}$$

As we have decentralized 1), 2), 3), 5), we can apply the same splitting to the 4th iteration as well:

$$\begin{aligned}
 V_{i \in \{1, \dots, n\}} z_i^{k+1} &= z_i^k + x_i^{k+1} - x_i^{k+1/2} \\
 &= z_i^k + \frac{1}{n} \sum_{i=1}^n x_i^{k+1/2} - x_i^{k+1/2} \\
 &= z_i^k + \frac{1}{n} \sum_{i=1}^n (x_i^{k+1} - z_i^{k+1}) - x_i^{k+1/2} \\
 &= z_i^k + \underbrace{\frac{1}{n} \sum_{i=1}^n x_i^{k+1/2}}_{\bar{x}^{k+1/2}} - \underbrace{\left(\frac{1}{n} \sum_{i=1}^n z_i^k \right)}_{\bar{z}^k} - x_i^{k+1/2}
 \end{aligned}$$

$$= z_i^k + \bar{z}_i^{-k+l} - \bar{z}^k - z_i^{k+l}$$

$\therefore \forall i \in \{1, \dots, m\} z_i^{k+1} = z_i^k + \frac{x_i - x_i^k}{n}$ note that \tilde{x}, \tilde{z} related iteratively
 #interested in $x = R_k(z)$, $z = C_k(x)$ in
 #the end, in our iteration for consensus optimization

$\forall i \in \{1, \dots, n\} z_i^{k+1} = z_i^k + \bar{x}^k - \bar{z}^k - x_i^k$ # note that x, z related here is state
 # ये प्राप्त होते हैं, और वे क्या हैं?
 # interested in $x = R_k(z)$, $z = C_k(x)$ in
 # the end, in our iteration for consensus optimization
 # we need only 1) and 4) in iteration.

In summary, D-R consensus iteration can be written as:

$\forall i \in \{1, \dots, n\}$

$$x_i^{k+1} = \underset{y_i}{\operatorname{argmin}} \left(f_i(y_i) + \frac{1}{\lambda} \|y_i - z_i^k\|_2^2 \right)$$

$$z_i^{k+1} = z_i^k + \bar{x}^{k+1} - \bar{z}^k - x_i^{k+1}$$

note that the entire process is
 # decentralized, there is no need for a central unit!
 # D-R consensus

$$\text{here } \bar{x}^{k+1} = \frac{1}{n} \sum_{i=1}^n x_i^{k+1}, \quad \bar{z}^k = \frac{1}{n} \sum_{i=1}^n z_i^k$$

* Distributed AP:

$$\begin{pmatrix} \lambda \sum_{i=1}^n \|A_i x - b_i\|_2^2 \\ \gamma \\ \forall i \in \{1, \dots, n\} f_i(x) \leq g_i \end{pmatrix} = \begin{pmatrix} \lambda \sum_{i=1}^n \|A_i x - b_i\|_2^2 + \sum_{i=1}^n \langle 0 | f_i - g_i \rangle(x) \\ \gamma \\ \forall i \in \{1, \dots, n\} f_i(x) \leq g_i \end{pmatrix} \quad \# y_i, y_j \text{ represent } x_i \text{ terms}$$

$$= \begin{pmatrix} \lambda \sum_{i=1}^n \left(\frac{1}{2} \|A_i x - b_i\|_2^2 + \langle 0 | f_i - g_i \rangle(x) \right) \\ \gamma \\ x \end{pmatrix}$$

Remember the key to distributed optimization is having uncoupled objective (See Primal Dual decomposition). Now in our case we do not have uncoupled objective, we uncouple them by providing local copy of the variable, and maintain the equality in terms of a consensus constraint such as $\text{local_copy_1} = \text{local_copy_2} = \dots = \text{local_copy_n}$

$$= \begin{pmatrix} \lambda \sum_{i=1}^n \|A_i y_i - b_i\|_2^2 \\ \gamma \\ \forall i \in \{1, \dots, n\} f_i(y_i) \leq g_i \\ y_1 = y_2 = \dots = y_n \# \text{ allows them equal to } x \\ \lambda \sum_{i=1}^n \|A_i x_i - b_i\|_2^2 + \sum_{i=1}^n \langle 0 | f_i - g_i \rangle(x_i) \\ 1 \quad x_1 = x_2 = \dots = x_n \end{pmatrix} \quad \# \text{ note } y_1, \dots, y_n \text{ are vectors themselves with same dimension as } x$$

$$= \begin{pmatrix} \lambda \sum_{i=1}^n \overbrace{\left(\frac{1}{2} \|A_i x_i - b_i\|_2^2 + \langle 0 | f_i - g_i \rangle(x_i) \right)}^{f_i(x_i)} \\ \gamma \\ x_1 = x_2 = \dots = x_n \end{pmatrix} \quad \# \text{ this form of the optimization}\\ \# \text{ problem is in the consensus optimization form } \# \text{ Consensus Optimization Problem}\\ \# \text{ so, we can apply D-R consensus } \# \text{ D-R consensus}$$

Then we will have the following optimization problem:

$\forall i \in \{1, \dots, n\}$

$$x_i^{k+1} = \underset{y_i}{\operatorname{argmin}} \left(f_i(y_i) + \frac{1}{\lambda} \|y_i - z_i^k\|_2^2 \right) = \underset{y_i}{\operatorname{argmin}} \left(\frac{1}{2} \|A_i y_i - b_i\|_2^2 + \langle 0 | f_i - g_i \rangle(y_i) + \frac{1}{\lambda} \|y_i - z_i^k\|_2^2 \right)$$

$$= \underset{y_i \in \{0 | f_i - g_i\}}{\operatorname{argmin}} \left(\frac{1}{2} \|A_i y_i - b_i\|_2^2 + \frac{1}{\lambda} \|y_i - z_i^k\|_2^2 \right)$$

$$z_i^{k+1} = z_i^k + \bar{x}^{k+1} - \bar{z}^k - x_i^{k+1}$$

(1)