

LINEARIZED SPLIT BREGMAN

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1. PROXIMITY OPERATOR

Firstly, Consider the following problem

$$(1) \quad \text{prox}_x = \arg \min_z \|x - z\|_2^2 + \lambda \|z\|_1$$

since all the functions in the problem are convex, the optimality condition is

$$0 \in \nabla(\|x - z\|_2^2) + \lambda \partial \|z\|_1$$

Notice that the above equation is just summation of each component, it is equivalent to considering an arbitrary i -th component. if $\|z_i\| \neq 0$, the subgradient of $|z_i|$ is just the gradient, which is $\text{sgn}(z_i)$, where z_i is one component of z , thus the above relation becomes the equality

$$(2) \quad 0 = 2(z_i - x_i) + \lambda \text{sgn}(z_i)$$

$$(3) \quad z_i = x_i - \frac{1}{2} \lambda \text{sgn}(z_i)$$

from above equation it is clear that if $z_i > 0$, x_i must be greater than 0, and if $z_i < 0$, $x_i < 0$ also holds. Hence $\text{sgn}(z_i) = \text{sgn}(x_i)$, in turn the following is true

$$(4) \quad z_i = x_i - \frac{1}{2} \lambda \text{sgn}(x_i)$$

For z_i equals 0 the subgradient of $|z_i|$ is the interval $[-1, 1]$,

$$0 \in 2(z_i - x_i) + \lambda[-1, 1] \Rightarrow x_i \in [-\frac{\lambda}{2}, \frac{\lambda}{2}]$$

Combine two cases, for each z_i the minimizer satisfy the following relation

$$(5) \quad z_i = \begin{cases} 0 & |x_i| \leq \frac{\lambda}{2} \\ x_i - \frac{1}{2} \lambda \text{sgn}(x_i) & |x_i| > \frac{\lambda}{2} \end{cases}$$

2. GENERAL LINEAR L_1 MINIMIZATION

In many applications, the problem can be formulized as

$$(6) \quad \arg \min_z \|Az - x\|_2^2 + \lambda \|z\|_1$$

where A is a linear operator. Approximate the above equation by Taylor expansion at z^k , the linearized version of the problem becomes an iterative scheme

$$(7) \quad z^{k+1} = \arg \min_z \lambda \|z\|_1 + \|Az^k - x\|_2^2 + (A^t Az^k - A^t x, z - z^k) + \frac{1}{2\delta} \|z - z^k\|^2$$

The last penalty term is to make sure z_{k+1} and z_k not too far from each other so that Taylor expansion is still valid. Throw away some constants, the scheme can be simplified as

$$(8) \quad z^{k+1} = \arg \min_z \lambda \|z\|_1 + \frac{1}{2\delta} \|z - (z^k - \delta(A^t Az^k - A^t x))\|^2$$

Note that the right hand side is of the form derived in Section 1, hence z^{k+1} can be solved as

$$(9) \quad z_i = \begin{cases} 0 & |y_i| \leq \lambda\delta \\ y_i - \frac{1}{2}\lambda \text{sgn}(y_i) & |y_i| > \lambda\delta \end{cases}$$

where $y_i = z_i^k - \delta(A^t Az_i^k - A^t x_i)$

3. LINEARIZED SPLIT BREGMAN AND AUGMENTED LAGRANGE METHOD

4. APPENDIX

subderivative