

Proximal Point Algorithm and Method of Multipliers

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Proximal_p
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def: monotone operators definitions and related

page1 Damped Cayley Iteration: Consider $F \in \text{monotone}$

$F(x) \ni 0$ solve $\partial f(x)$ b/c

\downarrow

$C(x) = x$ Why find fixed point of Cayley and resolvent of some monotone operator?

[# damped iteration for finding fixed point of nonexpansive mapping #]

now as C is a nonexpansive operator, so $x^{k+1} = C(x^k)$ might not converge, but damped iteration will work

$\{ \lambda \in [0,1], F \text{ monotone} \} \Rightarrow C \text{ nonexpansive function}$

$$x^{k+1} = \theta C(x^k) + (1-\theta)x^k \quad \theta \in (0,1)$$

$$= \theta (R(x^k) - x^k) + x^k - \theta x^k$$

$$= \theta R(x^k) - \theta x^k + x^k - \theta x^k$$

$$= \theta R(x^k) + (1-\theta)x^k$$

$$= \eta R(x^k) + (1-\eta)x^k \quad [\eta = \theta \in (0,1)]$$

this will converge! see the proof at [# damped iteration for finding fixed point of nonexpansive]

When, $\eta=1$, then:

$$x^{k+1} = \eta R(x^k) + (1-\eta)x^k = R(x^k) + 0x^k = R(x^k) \quad \text{// This is also called the}$$

$$x^{k+1} = R(x^k) \quad \text{[proximal point method]}$$

// proximal point algorithm, when $F = \partial f$ then

thm: proximal operator is the resolvent of subdifferential operator

turns into the proximal gradient algorithm

$F = \partial f$,

$\partial f(x)$

Will converge!

$$x^{k+1} = R(x^k) = \text{prox}_{f^*}(x^k) = \arg\min_x (f(x) + \frac{1}{2\lambda} \|x - x^k\|_2^2)$$

This is saying something very important, if C is nonexpansive then $x^{k+1} = R(x^k)$ will converge, as this is the damped Cayley iteration for specific parameter value!!! Or that, amra bolte pari, if F is monotone $\Rightarrow C$ is nonexpansive then $0 \in F(x)$ can be solved by solving $R(x) = x$, inspite of R being nonexpansive. This is a very special case, as for general nonexpansive operator O , $x^{k+1} = O(x^k)$ may not converge, but when $O = R$ it does!!! (I need to ensure this observation in future!)

$$\# 0 \in F(x) \Leftrightarrow R(x) = x$$

*Multiplier to residual mapping: (MRM mapping)

def: multiplier to residual mapping

resolvent for multiplier to residual mapping

By definition,

$$F(\theta) = b - A \arg\min_x L(x, \theta) \quad \text{# this is a monotone operator}$$

$$L(x, v) = f(x) + v^T(Ax - b)$$

$$\begin{pmatrix} f(x) \\ Ax = b \end{pmatrix} \quad \text{# The optimization problem in consideration}$$

$$\therefore 0 \in F(v) = b - A \arg\min_x L(x, v)$$

Will produce $x^*(v)$ optimal primal variable as a function of v

so a $0 \in F(v^*)$ means we also have the optimal dual variable,

so, $x^*(v^*) = x^*$ will be the optimal primal variable.

Why find fixed point of Cayley and resolvent of some monotone operator?

now from the resolvent-monotone operator relation (see atf):

$R(v) = v$ will give the v^* , as MRM is monotone, and for $\lambda \geq 0$, its resolvent is nonexpansive

atf atf,

resolvent for multiplier to residual mapping (see atf)

$\therefore R(v) = z$ can be determined from:

$\therefore R(y) = z$ can be determined from:

$$x := \underset{w}{\operatorname{argmin}} \left(f(w) + y^T(Aw - b) + \frac{\lambda}{2} \|Aw - b\|_2^2 \right)$$

$$z := y + \lambda(Ax - b)$$

say $R(y^*) = y^*$

* now when we are interested in finding the fixed point of R , then we can use the iteration:

$$R(y^k) = y^{k+1}$$

Because, if F monotone, $\lambda \geq 0$ then $R = (I + \lambda F)^{-1}$: nonexpansive

As resolvent is an exceptional nonexpansive function that does not require damped iteration, normal contraction like iteration is sufficient to find the fixed point. So, we can use $x^{k+1} = R(x^k)$ to find the fixed point.

$$y := y^k$$

$$z := y^{k+1}$$

ଆମେ ଏହା:

$x := x^{k+1}$ # this is for just keeping track

$$x^{k+1} := \underset{w}{\operatorname{argmin}} \left(f(w) + y^T(Aw - b) + \frac{\lambda}{2} \|Aw - b\|_2^2 \right)$$

$$y^{k+1} := y^k + \lambda(Ax^{k+1} - b)$$

old explanation, can be ignored

MRM's resolvent's fixedpoint (ଆମେ ଏହା) by using the following formula:

$$R(y) = y$$

$$x = \underset{w}{\operatorname{argmin}} \left(f(w) + y^T(Aw - b) + \frac{\lambda}{2} \|Aw - b\|_2^2 \right)$$

$$y = y + \lambda(Ax - b)$$

$$\left(R \begin{pmatrix} x \\ y \end{pmatrix} \right)$$

here $\begin{pmatrix} x \\ y \end{pmatrix}$ is the structure of the input argument of the resolvent

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} \underset{w}{\operatorname{argmin}} \left(f(w) + y^T(Aw - b) + \frac{\lambda}{2} \|Aw - b\|_2^2 \right) \\ y + \lambda(Ax - b) \end{bmatrix}$$

note: technically y is also y^k . y is also y^k

$x = \underset{w}{\operatorname{argmin}} (\cdot)$ is also x^k , so R is essentially is a block

operator operating on both x and y , and we have already

proven MRM is monotone, hence for $\lambda \geq 0$, its resolvent is

nonexpansive.

So, by using proximal point algorithm: $\begin{bmatrix} x^{k+1} \\ y^{k+1} \end{bmatrix} = \left(R \begin{pmatrix} x \\ y \end{pmatrix} \right) \begin{bmatrix} x^k \\ y^k \end{bmatrix}$

$$\begin{bmatrix} x^{k+1} \\ y^{k+1} \end{bmatrix} = \begin{bmatrix} \underset{w}{\operatorname{argmin}} \left(f(w) + y^T(Aw - b) + \frac{\lambda}{2} \|Aw - b\|_2^2 \right) \\ y + \lambda(Ax - b) \end{bmatrix} \begin{bmatrix} x^k \\ y^k \end{bmatrix}$$

$$\Leftrightarrow \begin{bmatrix} x^{k+1} \\ y^{k+1} \end{bmatrix} = \begin{bmatrix} \underset{w}{\operatorname{argmin}} \left(f(w) + (y^k)^T(Aw - b) + \frac{\lambda}{2} \|Aw - b\|_2^2 \right) \\ y^k + \lambda(Ax^k - b) \end{bmatrix}$$

Method of multipliers

$$x^{k+1} = \underset{w}{\operatorname{argmin}} \left(f(w) + (y^k)^T(Aw - b) + \frac{\lambda}{2} \|Aw - b\|_2^2 \right)$$

$$y^{k+1} = y^k + \lambda(Ax^k - b)$$

Will converge to primal dual pair

eq: method of multipliers

// if $f(\cdot)$ is not strictly convex, then '=' is replaced by ' \in '

So, primal feasibility occurs as $k \rightarrow \infty$

the first stage is augmented Lagrangian minimization, $x^k \hookrightarrow x^*$, so $Ax^k - b \hookrightarrow 0$

the second stage is update the dual variable, $y^k \hookrightarrow y^*$

the second stage is update the dual variable, $y^k \leftarrow y^*$

Method of multipliers, though like dual method,

- uses augmented Lagrangian
- converges under far more general conditions (than dual method)
- f can be non differentiable, can be $+\infty$
- disadvantage: in this form not easy to decompose.