

## 董云达的代表作系列一

**董氏引理** 设  $\{\alpha_k\}, \{\beta_k\}, \{\gamma_k\}$  是三个正序列。假设它们满足：

$$\alpha_{k+1}^2 \leq \alpha_k^2 - \beta_k \gamma_k, \quad k = 0, 1, \dots,$$

且序列  $\{\beta_k\}$  是不可和的，序列  $\{\gamma_k\}$  单调递减。那么，存在序列  $\{\varepsilon_k\}$  使得下述关系成立：

$$\gamma_k \sum_{i=0}^k \beta_i \leq 2\alpha_0 \varepsilon_k,$$

$$\alpha_k \leq \varepsilon_k \leq \alpha_0, \quad \lim_{k \rightarrow +\infty} \varepsilon_k = \lim_{k \rightarrow +\infty} \alpha_k.$$

Brezis 与菲尔兹奖获得者 Lions 证明邻近点方法收敛率与  $1/k$  的同阶。董氏引理进一步将其提升至高阶无穷小。截至2024年末，该成果已被下载超4000次！



值得指出的是，利用董氏引理可以证明 Abel-Dini 定理。

## 董云达的代表作系列二

假设  $f$  在欧氏空间中是二次连续可微的凸函数。考虑无约束极小化问题  $\min f(x)$ 。相应的拟 Newton 法为

$$x^{k+1} = x^k - \alpha_k W_k \nabla f(x^k),$$

其中  $W_k$  由某个对称秩二校正公式自动生成，而  $\alpha_k$  作为步长由下面 Wolfe 条件确定

$$\begin{aligned} f(x + \alpha d) &\leq f(x) + c_1 \alpha \nabla f(x)^T d, \\ \nabla f(x + \alpha d)^T d &\geq c_2 \nabla f(x)^T d, \end{aligned}$$

其中  $0 < c_1 < c_2 < 1$ 。

在 2007-2010 年间，董云达提出了董氏条件

$$c_2 \nabla f(x)^T d \leq \nabla f(x + \alpha d)^T d \leq c_1 \nabla f(x)^T d, \quad 0 < c_1 < c_2 < 1.$$

对于董氏条件，2020年德国卡尔斯鲁厄理工学院（德国版MIT）的学者在计算力学顶刊 Comput Method Appl M 上予以好评：“与 Wolfe 条件形成鲜明对比的是，董氏条件仅仅依赖梯度的估值...”

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iteration reads

$$x^{k+1} = x^k - a^k \mathcal{H}^{-1}(x^k) \nabla f(x^k)$$

with the Hessian  $\mathcal{H}$  of  $f$  and a damping factor  $a^k \in (0, 1]$ , cf. Chapter 9 in Boyd's book [60]. Instead of inverting  $\mathcal{H}(x^k)$ , the update can be performed by

$$x^{k+1} = x^k + a^k \Delta x$$

where  $\Delta x$  is an approximate solution of

$$\mathcal{H}(x^k) \Delta x = -\nabla f(x^k). \quad (5.10)$$

The damping factor  $a^k$  is determined by a back-tracking procedure. In this paper, we use the stopping criteria of Dong [63]

$$c_2 \langle \nabla f(x^k), \Delta x \rangle_V \leq \langle \nabla f(x^k + a^k \Delta x), \Delta x \rangle_V \leq c_1 \langle \nabla f(x^k), \Delta x \rangle_V$$

with  $0 < c_1 < c_2 < 1$ . In contrast to the Wolfe conditions [64], Dong's criteria rely solely on gradient evaluations. This is beneficial, as evaluating  $f$  requires either the primal or dual condensed incremental potential, cf. Table 1, which is generally not available in FFT-based homogenization. Both  $w$  and  $w^*$  carry no physical meaning as they

## 董云达的代表作系列三

在 2003 年博士论文的第四章，董云达在 Hilbert 空间中考虑了下面的问题

$$0 \in Mx + q + B(x),$$

其中  $M$  是有界、线性和单调的， $q$  是一个向量， $B$  是极大单调的，并且提出了下面的方法

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**Algorithm 4.2.1.** Let  $F(x) = Mx + q$ . Choose any starting point  $x^0 \in \mathcal{H}$ .  
For any given  $k \geq 0$ , computing  $x^{k+1}$  from  $x^k$  according to

$$x^{k+1} = x^k - \gamma_k(I + M^T)r(x^k) \quad \forall k \geq 0. \quad (4.9)$$

where

$$\begin{aligned} r(x) &= x - (I + B)^{-1}(x - Mx - q), \\ \gamma_k &= \|(I + M^T)r(x^k)\|^{-2} \|r(x^k)\|^2. \end{aligned} \quad (4.10)$$

更多细节参考 <https://ydong2024.github.io/downloads/dongthesis.pdf>

该结果发表在 Appl Math Letters (2005)，2024年获排名第一的数学顶刊 Acta Numerica 的好评。

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sequence in  $[\varepsilon, 2 - \varepsilon]$ , let  $x_0 \in \mathcal{H}$ , and let  $y_0^* \in \mathcal{G}$ . Iterate

$$\begin{aligned} &\text{for } n = 0, 1, \dots \\ &\quad \begin{cases} a_n = J_{\gamma_n A}(x_n - \gamma_n L^* y_n^*) \\ l_n = Lx_n \\ b_n = J_{\sigma_n B}(l_n + \sigma_n y_n^*) \\ t_n = b_n - La_n \\ t_n^* = \gamma_n^{-1}(x_n - a_n) + \sigma_n^{-1} L^*(l_n - b_n) \\ \tau_n = \|t_n\|^2 + \|t_n^*\|^2 \\ \text{if } \tau_n > 0 \\ \quad \theta_n = \lambda_n(\gamma_n^{-1} \|x_n - a_n\|^2 + \sigma_n^{-1} \|l_n - b_n\|^2) / \tau_n \\ \text{else } \theta_n = 0 \\ x_{n+1} = x_n - \theta_n t_n^* \\ y_{n+1}^* = y_n^* - \theta_n t_n. \end{cases} \end{aligned} \quad (9.11)$$

Then  $(x_n)_{n \in \mathbb{N}}$  converges weakly to a point  $x \in Z$  and  $(y_n^*)_{n \in \mathbb{N}}$  converges weakly to a point  $y^* \in Z^*$ .

**Remark 9.2.** Here are notable instantiations of Proposition 9.1.

- (i) The first instance of (9.11) in the literature seems to be that of Dong (2005), where  $\mathcal{H}$  and  $\mathcal{G}$  are Euclidean spaces,  $A = 0$ , and  $(\forall n \in \mathbb{N}) \gamma_n = \sigma_n = 1$  and  $\lambda_n = \lambda \in ]0, 2[$ . Convergence of the primal sequence  $(x_n)_{n \in \mathbb{N}}$  was established by different means.

## 董云达的代表作系列四

在 2003 年博士论文的第四章，董云达在 Hilbert 空间中考虑了下面的问题

$$0 \in F(x) + B(x),$$

其中  $F$  是连续单调的， $B$  是极大单调的。利用图(a)中的记号  $J_\lambda(x)$ ，提出了下面的方法

*Proof.* Since  $J_\lambda(x) := (I + \lambda B)^{-1}(I - \lambda F)(x)$ , we have

$$J_\lambda(x) + \lambda B(J_\lambda(x)) \ni x - \lambda F(x).$$

That is,

$$\lambda^{-1}(x - J_\lambda(x)) - F(x) \in B(J_\lambda(x)). \quad (4.3)$$

On the other hand, since  $z$  is a zero of  $T := B + F$  then we have

$$-F(z) \in B(z) \quad (4.4)$$

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**Algorithm 4.2.4.** Choose any starting point  $x^0 \in \mathcal{H}$  and  $\lambda_{-1} \in (0, +\infty)$ . Also choose  $\rho \in (0, 1)$  and  $\beta \in (0, 1)$ . For any given  $k \geq 0$ , computing  $(x^{k+1}, \lambda_k)$  from  $(x^k, \lambda_{k-1})$  where  $\lambda_k$  is the largest  $\lambda \in \{\lambda_{k-1}, \lambda_{k-1}\beta, \lambda_{k-1}\beta^2, \dots\}$  satisfying

$$\lambda \langle x^k - J_\lambda(x^k), F(x^k) - F(J_\lambda(x^k)) \rangle \leq (1 - \rho) \|x^k - J_\lambda(x^k)\|^2,$$

and let

$$x^{k+1} = x^k - \gamma_k(x^k - J_{\lambda_k}(x^k) - \lambda_k F(x^k) + \lambda_k F(J_{\lambda_k}(x^k))) \quad \forall k \geq 0,$$

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(a)

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(b)

更多细节参考 <https://ydong2024.github.io/downloads/dongthesis.pdf>

将上边的  $B$  和  $J_\lambda(x)$  分别换成  $A$  和  $x(\alpha)$ ，利用董云达论文 [Math Comput Simulat, 223, 86-107, 2024] 中的记号，我们将其重新叙述/摘录如下：

Choose  $x^0 \in \text{dom}F \cap \text{dom}A$ . Choose  $\rho \in (0, 1)$  and  $\alpha_{-1} > 0$ . At  $k$ -th iteration, find the smallest  $j_k$  in  $\alpha = \alpha_{k-1} 0.5^{j_k}$ ,  $j = 0, 1, \dots$ , such that  $x^k(\alpha) = (I + \alpha A)^{-1}(x^k - \alpha F(x^k))$  satisfies

$$\alpha \langle x^k - x^k(\alpha), F(x^k) - F(x^k(\alpha)) \rangle \leq (1 - \rho) \|x^k - x^k(\alpha)\|^2.$$

Take  $\alpha_k = \alpha_{k-1} 0.5^{j_k}$ , and compute  $\bar{x}^k = x^k(\alpha_k)$ . Compute in order

$$d^k = x^k - \bar{x}^k - \alpha_k(F(x^k) - F(\bar{x}^k)), \quad \gamma_k = \langle x^k - \bar{x}^k, d^k \rangle / \|d^k\|^2.$$

Then choose  $\theta_k \in (0, 2]$  and compute

$$x^{k+1} = x^k - \theta_k \gamma_k d^k.$$

由于不需要估计 Lipschitz 常数以及克服了 Tseng 方法的小步长现象，从而成为求解上述问题的最实用的基本方法。2014年董云达与学生合作，通过具体例子，证实了它在数值方面的明显优势。2024年这篇论文，还讨论了  $F$  仅为一致连续的情形，并给出方法弱收敛性的一个严格证明。

至于凸极小化问题  $\min f(x) + g(x)$ ，我们考虑考虑其最优性条件

$$0 \in \nabla f(x) + \partial g(x),$$

并且取  $F := \nabla f$  以及  $A := \partial g$  即可。

## 董云达的代表作系列五

董云达在论文 [Math Comput Simulat, 223, 86-107, 2024] 中考虑了下面的问题

$$0 \in F(x) + A(x) + Q^*B(Qx - q),$$

其中  $F$  是连续单调的,  $A, B$  是极大单调的,  $Q$  是线性的而  $Q^*$  是它的伴随,  $q$  是一个向量, 并且提出了一个新的实用算法

In the case of  $F_i$  being Lipschitz continuous, we give

**Algorithm 2.1.** Our proposed splitting algorithm in Lipschitz continuity case

Step 0. For  $i = 1, \dots, n$ , choose  $x_i^0 \in \mathcal{H}_i$ ,  $u^0 \in \mathcal{G}$ . Choose  $\alpha_{i,-1} > 0$ ,  $\rho \in (0, 1)$ . Set  $k := 0$ .

Step 1. For  $i = 1, \dots, l$ , choose appropriate  $\alpha_{i,k} > 0$ . For  $i = l + 1, \dots, n$ , find the smallest  $j_k$  in (19) such that

$$x_i^k(\alpha_i) = (I + \alpha_i A_i)^{-1}(x_i^k - \alpha_i(F_i(x_i^k) + Q_i^* u^k))$$

satisfies

$$\alpha_i \langle x_i^k - x_i^k(\alpha_i), F_i(x_i^k) - F_i(x_i^k(\alpha_i)) \rangle \leq (1 - \rho) \|x_i^k - x_i^k(\alpha_i)\|^2. \quad (20)$$

Take  $\alpha_{i,k} = \alpha_{i,k-1} t^{j_k}$ , and compute

$$\bar{x}_i^k = x_i^k(\alpha_{i,k}). \quad (21)$$

Choose  $\beta_k > 0$  via (29) below and find  $\bar{u}^k$  such that

$$(\beta_k I + B^{-1})(\bar{u}^k) \ni \beta_k u^k + \sum_{i=1}^n Q_i \bar{x}_i^k - q. \quad (22)$$

If  $\bar{x}_i^k = x_i^k$ ,  $i = 1, \dots, n$ , and  $\bar{u}^k = u^k$ , then stop. Otherwise go to Step 2.

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Step 2. For  $i = 1, \dots, n$ , compute

$$d_{x_i}^k = \alpha_{i,k}^{-1}(x_i^k - \bar{x}_i^k) - (F_i(x_i^k) - F_i(\bar{x}_i^k)) - Q_i^*(u^k - \bar{u}^k), \quad (23)$$

$$d_u^k = \beta_k(u^k - \bar{u}^k), \quad (24)$$

$$\gamma_k = \frac{\sum_{i=1}^n \langle x_i^k - \bar{x}_i^k, d_{x_i}^k \rangle + \langle u^k - \bar{u}^k, d_u^k \rangle}{\sum_{i=1}^n \|d_{x_i}^k\|^2 + \|d_u^k\|^2}. \quad (25)$$

Then choose  $\theta_k \in (0, 2]$  and the new iterates are given by

$$x_i^{k+1} = x_i^k - \theta_k \gamma_k d_{x_i}^k, \quad i = 1, \dots, n, \quad (26)$$

$$u^{k+1} = u^k - \theta_k \gamma_k d_u^k. \quad (27)$$

Set  $k := k + 1$ , and go to Step 1.

它是“董云达的代表作系列四”中方法的一个拓展, 尤其适用于高光谱解混、深度学习中的特征选取等前沿问题。更多细节参考

<https://ydong2024.github.io/downloads/journal2024.pdf>