Enlarged Krylov methods and 2-level preconditioner for the map-making problem in CMB data analysis

Modelling 2019 - Olomouc

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The Cosmic Microwave Background and MM problem

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Relic radiation \rightarrow First photons that started to travel in the very early hot and dense universe (379,000 years old out of 13.8 billions)

The goal : Reconstruct a map of temperature and polarisation of these early photons



Figure 1: Evolution of the CMB map of temperature



Figure 2: Map of temperature reconstructed from nine years of WMAP data satellite (2003-2012)



Figure 3: Map of temperature with Planck satellite

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Maximum likelihood estimate, \hat{s} , of the signal s given by :

$$\underbrace{\left(\underline{P^t N^{-1} P}\right)}_{A} \hat{s} = P^t N^{-1} d$$

Where $N \in \mathbb{R}^{n_t \times n_t}$ is the covariance matrix of the noise.

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The way we observe the sky, encoded by the pointing matrix $\ensuremath{\boldsymbol{P}}$ as such :

A line numbered $1 \le i \le n_t$ of P, $P_{i,.} \in \mathbb{R}^{n_p}$, says what pixels we look at time i

 $P_{i,.} = (0, ..., 0, t_i, 0, ..., 0)$ (1)

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⁽¹⁾

Particular case : when polarization added, pixel domain*3 and lines of $P \in \mathbb{R}^{n_t \times 3n_p}$ became :

$$P_{i,.} = (0, ..., 0, t_i, q_i, u_i, 0, ..., 0)$$
(2)

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 2 ≤ k ≤ λ_l the off-diagonal coef. of block l, λ_l being the band width

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$$N^{-1} = \begin{bmatrix} N_1^{-1} & 0 & \cdots & 0 \\ 0 & N_2^{-1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & N_{n_{blc}}^{-1} \end{bmatrix}$$

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with block like this :



From CG to Enlarged-CG

Define T_t , for $t \in \mathbb{N}$ the splitting parameter :

$$T_t: \begin{array}{c} \mathbb{R}^n \to \mathbb{R}^{n \times t} \\ x \mapsto T_t(x) \end{array}$$
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$$x = \begin{pmatrix} * \\ * \\ \vdots \\ * \\ * \\ * \\ * \end{pmatrix} \mapsto T_t(x) = \begin{pmatrix} * & 0 \\ * & \vdots \\ 0 & \dots & * \\ \vdots & \vdots \\ 0 & & * \end{pmatrix}$$

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Enlarged the Krylov space with T_t :

$$K_{k,t} = \mathsf{Span}_{\Box}\left(T_t(r_0), AT_t(r_0), ..., A^{k-1}T_t(r_0)\right)$$

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$$\mathcal{K}_{k,t} = \mathsf{Span}_{\Box}\left(\mathcal{T}_t(r_0), \mathcal{AT}_t(r_0), ..., \mathcal{A}^{k-1}\mathcal{T}_t(r_0)\right)$$

For $x_0 \in \mathbb{R}^{n imes t}$, build the sequence $(x_k)_{k \ge 0}$ s.t. :

$$\begin{cases} x_{k+1} \in x_0 + K_{k,t} \\ r_{k+1} = b - Ax_k \perp K_{k,t} \end{cases}$$
(4)

Lemma

For x_k the k-th approximation build from (4), x_{k+1} satisfies :

$$K_k \subset K_{k,t}$$

$$||x_{k+1} - \underline{x}||_A = \min_{x \in x_0 + K_{k,t}} ||x - \underline{x}||_A$$

Theorem (O. Tissot, L. Grigori)

Let x_k be the k-th iterate build with (10), then we have :

$$||x_k - \underline{x}||_A \le C \left(\frac{\sqrt{\kappa_t} - 1}{\sqrt{\kappa_t} + 1}\right)^k$$
 (5)

with $\kappa_t = \lambda_n / \lambda_t$ where λ_t is the t^{th} smallest eigenvalue of A and C is a constant independent of k.

Algorithm 1 Enlarged CG **Require:** $A \in \mathbb{R}^{n \times n}, b \in \mathbb{R}^n, x_0 \in \mathbb{R}^n, k_{max} \in \mathbb{N}, \varepsilon > 0, t \in \mathbb{N}$ **Ensure:** $||b - Ax_k||_2 < \varepsilon ||b||_2$ or $k = k_{max}$ $k = 0, p_0 = r_0 = b - Ax_0$ $X_0 = T_t(x_0), P_0 = T_t(p_0), R_0 = T_t(r_0)$ while $||r_{k+1}|| > \varepsilon ||b||$ ou $k < k_{max}$ do A-orthonormalize P_k $\alpha_{k} = P_{k}^{t}R_{k}$ $X_{k+1} = X_k + P_k \alpha_k$ $R_{k+1} = R_k - A P_k \alpha_k$ $r_{k+1} = R_{k+1} \mathbf{1}_t$ $P_{k+1} = R_{k+1} - P_k P_k^{\top} A R_{k+1}$ k = k + 1end while Return $x_{k+1} = X_{k+1} * \mathbf{1}_t$

A few numerical results



Figure 4: Tim Davis' collection + 3D elasticity problem, O. Tissot



Figure 5: Map-Making ORTHODIR case8

2-level preconditioner from fictitious space lemma

Lemma

 $(H, (., .)), (H_D, (., .)_D)$ two Hilbert spaces, two symmetric positive bilinear forms $a : H \times H \longrightarrow \mathbb{R}$, $b : H_D \times H_D \longrightarrow \mathbb{R}$, generated by the SPD operators $\mathcal{A} : H \longrightarrow H$ and $B : H_D \longrightarrow H_D$, respectively. Suppose that there exists a linear operator $\mathcal{R} : H_D \longrightarrow H$ such that the following holds :

• \mathcal{R} is surjective.

•
$$\exists c_U \text{ s.t. } \forall u_D \in H_D, a(\mathcal{R}u_D, \mathcal{R}u_D) \leq c_U b(u_D, u_D)$$

•
$$\exists c_L \text{ s.t. } \forall u \in H, \exists u_D \in H_D \text{ s.t. } \mathcal{R}u_D = u,$$

 $c_L b(u_D, u_D) \leq a(\mathcal{R}u_D, \mathcal{R}u_D) = a(u, u)$

 $\mathcal{R}^*: H \longrightarrow H_D$ the adjoint operator of $\mathcal{R},$ then :

$$\Lambda\left(\mathcal{R}B^{-1}\mathcal{R}^*\mathcal{A}\right)\subset\left[c_L,c_U\right]$$

• n_{blc} blocks of N^{-1} splits $\{1, ..., n_t\}$ in n_{blc} domains :

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$$\mathcal{R}: \begin{array}{c} H_D \longrightarrow H \\ (u_l)_{l=0\dots N} \mapsto \sum_{l=0}^N P_l^\top u_l \end{array}$$

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Lemma (Surjectivity of \mathcal{R})

 ${\mathcal R}$ define as such is surjective.

• Define operators *a* and *b* :

$$a: \begin{array}{c} H \times H \longrightarrow \mathbb{R} \\ (u, v) \mapsto a(u, v) := u^{\top} A v \\ b: \begin{array}{c} H_D \times H_D \longrightarrow \mathbb{R} \\ (\mathcal{U}, \mathcal{V}) \mapsto b(\mathcal{U}, \mathcal{V}) := \mathcal{U}^{\top} B \mathcal{V} \end{array}$$

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$$\begin{array}{l} \mathsf{H} \times \mathsf{H} \longrightarrow \mathbb{R} \\ \mathsf{a} : & (u, v) \mapsto \mathsf{a}(u, v) := u^{\top} \mathsf{A} v \\ & b : & \mathsf{H}_D \times \mathsf{H}_D \longrightarrow \mathbb{R} \\ & (\mathcal{U}, \mathcal{V}) \mapsto \mathsf{b}(\mathcal{U}, \mathcal{V}) := \mathcal{U}^{\top} \mathcal{B} \mathcal{V} \\ \mathcal{B}(\mathcal{U}) := & \left(\mathcal{P}_0^{\top} \mathcal{A} \mathcal{P}_0 u_0, \operatorname{diag}(\mathcal{N}_1^{-1}) u_1, ..., \operatorname{diag}(\mathcal{N}_{n_{blc}}^{-1}) u_{n_{blc}} \right) \\ \mathcal{B}^{-1}(\mathcal{U}) := \\ & \left((\mathcal{P}_0^{\top} \mathcal{A} \mathcal{P}_0)^{-1} u_0, \operatorname{diag}(\mathcal{N}_1^{-1})^{-1} u_1, ..., \operatorname{diag}(\mathcal{N}_{n_{blc}}^{-1})^{-1} u_{n_{blc}} \right) \end{array}$$

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$$\begin{array}{l} \mathcal{B}(\mathcal{U}) := & (\mathsf{P}_{0}^{\top} \mathcal{A} \mathsf{P}_{0} u_{0}, \operatorname{diag}(\mathcal{N}_{1}^{-1}) u_{1}, ..., \operatorname{diag}(\mathcal{N}_{n_{blc}}^{-1}) u_{n_{blc}}) \\ \mathcal{B}^{-1}(\mathcal{U}) := & \\ & ((\mathsf{P}_{0}^{\top} \mathcal{A} \mathsf{P}_{0})^{-1} u_{0}, \operatorname{diag}(\mathcal{N}_{1}^{-1})^{-1} u_{1}, ..., \operatorname{diag}(\mathcal{N}_{n_{blc}}^{-1})^{-1} u_{n_{blc}}) \\ & \mathsf{Set} \text{ the preconditioner } \mathcal{M}_{2}^{-1} : \end{array}$$

$$M_2^{-1} = \mathcal{R}B^{-1}\mathcal{R}^* = P_0(P_0^{ op}MP_0)^{-1}P_0^{ op} + P^{ op}diag(\mathcal{N}^{-1})^{-1}P_0^{ op}$$

Lemma (Continuity of \mathcal{R})

As such : $\exists c_U \text{ s.t. } \forall u_D \in H_D, a(\mathcal{R}u_D, \mathcal{R}u_D) \leq c_U b(u_D, u_D)$

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This result uses :

• for all $u_D \in H_D$:

 $u_D^{ op} N^{-1} u_D \leq K u_D^{ op} diag(N^{-1}) u_D$

Coarse space correction :

GenEO preconditioner : Neumann matrices *Ãⁱ*, uses PDE setting

$$\sum_{i=1}^{N} (R_{j}U)^{\top} \tilde{A}^{j} R_{j}U \leq k_{1}U^{\top} A U$$

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 ALS preconditioner : ALS of matrix A, A^j, uses operator *R* of DD

 Interview

$$\sum_{i=1}^{N} U^{\top} \tilde{A}^{i} U \leq k_{m} U^{\top} A U$$

In map-making :
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- Implement those two methods on highly parallel architure.

References

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Thank you for you attention !