

Lecture 23:

Recall:

Conjugate gradient method

Goal: Minimize a quadratic functional.

$$\vec{x}_* = \operatorname{argmin}_{\vec{x} \in \mathbb{R}^n} \varphi(\vec{x}) \quad ; \quad \varphi(\vec{x}) = \frac{1}{2} \vec{x}^T A \vec{x} - \vec{b}^T \vec{x}$$

where $A =$ symmetric positive definite matrix in $M_{n \times n}(\mathbb{R})$ and $\vec{b} \in \mathbb{R}^n$.

Recall: $\nabla \varphi(\vec{x}) = A\vec{x} - \vec{b}$ and $\underbrace{\varphi''(\vec{x})}_{\text{Hessian}} = A$

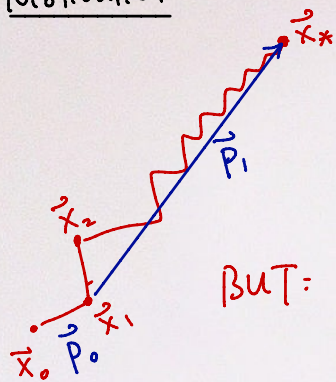
Minimizer \vec{x}^* of $\varphi(\vec{x})$ satisfies $A\vec{x}^* = \vec{b} \iff \left(\frac{\partial^2 \varphi}{\partial x_i \partial x_j} \right)$

Strategy: Given a current approximation \vec{x}_k , find a new approximation

by: $\vec{x}_{k+1} = \vec{x}_k + \alpha_k \vec{p}_k$ $\left(\begin{array}{l} \vec{p}_k = \text{search direction} \\ \alpha_k = \text{time step} \end{array} \right)$

But we want to choose: time step α_k to be the optimal and search direction such that $\vec{p}_i \cdot A \vec{p}_j = 0$ for $i \neq j$.

Motivation:



For $A \in M_{2 \times 2}(\mathbb{R})$, if \vec{x}^* = sol of $A\vec{x} = \vec{b}$.

Ideally, we want to find \vec{p}_1 such that the direction allows us to move directly to \vec{x}^* .

$$\therefore \vec{p}_1 \parallel \vec{x}^* - \vec{x}_1 \Rightarrow \vec{p}_1 = c(\vec{x}^* - \vec{x}_1)$$

BUT: $A\vec{p}_1 = \underset{\uparrow \mathbb{R}}{c} (A\vec{x}^* - A\vec{x}_1) = \underset{\uparrow \mathbb{R}}{c} (\vec{b} - A\vec{x}_1)$

$$A\vec{p}_1 \cdot \vec{p}_0 = \underbrace{c(\vec{b} - A\vec{x}_1)}_{-\nabla\psi(\vec{x}_1)} \cdot \vec{p}_0 = -c \nabla\psi(\vec{x}_0 + \alpha_0 \vec{p}_0) \cdot \vec{p}_0 = -c \left. \frac{d}{d\alpha} \right|_{\alpha=\alpha_0} \psi(\vec{x}_0 + \alpha \vec{p}_0) = 0$$

$$\therefore A\vec{p}_1 \cdot \vec{p}_0 = 0$$

Get convergence in JUST 2 steps!!

Summary: Find search ^① directions \vec{p}_j ($j=0, 1, 2, \dots$) such that
(Goal:) $\vec{p}_j^T A \vec{p}_k = 0$ for $j \neq k$ and find optimal time ^②
step α_j .

Definition: We say that the set of directions $\{\vec{p}_j\}_{j=0}^{k-1}$ is a
conjugate set of directions (with respect to A) if:

$$\vec{p}_j^T A \vec{p}_i = 0 \text{ for all } 1 \leq i, j \leq k-1 \text{ and } i \neq j.$$

Remark: $\because A$ is symmetric

$$\therefore \vec{p}_j^T A \vec{p}_i = \vec{p}_i^T A^T \vec{p}_j = \vec{p}_i^T A \vec{p}_j$$

Notation: $W_k \stackrel{\text{def}}{=} \text{span} \{ \vec{p}_0, \vec{p}_1, \dots, \vec{p}_{k-1} \}$

Choice of time step α_k (Given $\vec{p}_0, \vec{p}_1, \dots, \vec{p}_k$)

Optimal α_k :

$$\Psi(\vec{x}_k + \alpha \vec{p}_k) = \Psi(\vec{x}_k) + \alpha \nabla \Psi(\vec{x}_k) \cdot \vec{p}_k + \frac{\alpha^2}{2} \vec{p}_k^T A \vec{p}_k$$

(Taylor expansion)

Minimum attained at $\alpha = \frac{-\nabla \Psi(\vec{x}_k) \cdot \vec{p}_k}{\vec{p}_k^T A \vec{p}_k}$

\therefore we choose $\alpha_k = \frac{-\vec{r}_k \cdot \vec{p}_k}{\langle \vec{p}_k, \vec{p}_k \rangle_A}$

where $\vec{r}_k = A \vec{x}_k - \vec{b}$ and $\langle \vec{u}, \vec{v} \rangle_A \stackrel{\text{def}}{=} \vec{u} \cdot A \vec{v}$.

Choice of the search directions \vec{p}_j ($j=0,1,2,\dots$)

Suppose $\vec{p}_0, \vec{p}_1, \dots, \vec{p}_{k-1}$ are known. Then, we proceed to find the search direction \vec{p}_k in the form:

$$\vec{p}_k = -\vec{r}_k - \beta_{k-1} \vec{p}_{k-1} \quad \text{where} \quad \beta_{k-1} = -\frac{\vec{p}_{k-1}^T A \vec{r}_k}{\vec{p}_{k-1}^T A \vec{p}_{k-1}}$$

$$\Rightarrow A \vec{p}_k = -A \vec{r}_k - \beta_{k-1} A \vec{p}_{k-1}$$

$$\Rightarrow \vec{p}_{k-1}^T A \vec{p}_k = -\vec{p}_{k-1}^T A \vec{r}_k - \beta_{k-1} \vec{p}_{k-1}^T A \vec{p}_{k-1}$$

$$\begin{array}{l} \text{"} \\ \text{0} \\ \Rightarrow \end{array} \beta_{k-1} = -\frac{\vec{p}_{k-1}^T A \vec{r}_k}{\vec{p}_{k-1}^T A \vec{p}_{k-1}}$$

Next: We need to show: with the above recursive scheme to obtain $\{\vec{p}_j\}_{j=0}^{\infty}$;

(i) $\{\vec{p}_j\}$ are conjugate to each others.

(ii) $\vec{r}_i \cdot \vec{r}_j = 0$ for $i \neq j$.

$$(\vec{r}_i = A\vec{x}_i - \vec{b})$$

} Next time.

If the above are true, then we have:

Theorem: Consider the iterative scheme:

$$\vec{x}_{k+1} = \vec{x}_k + \alpha_k \vec{p}_k \quad (k=0, 1, 2, \dots)$$

Suppose $\{\vec{r}_k\}_{k=0}^{\infty}$ are orthogonal to each others ($\vec{r}_i \cdot \vec{r}_j = 0$ for $i \neq j$)

Then, the iterative scheme converges to the sol $A\vec{x} = \vec{b}$ in less

than \wedge n iterations.
or equal to

Proof: Suppose $\vec{r}_0, \vec{r}_1, \dots, \vec{r}_n$ are all non-zero.

Then: $\{\vec{r}_0, \dots, \vec{r}_n\}$ form an orthogonal $(\vec{r}_i \stackrel{\text{def}}{=} A\vec{x}_i - \vec{b})$

and lin. independent set in \mathbb{R}^n . (contradiction,
with $n+1$ elements)

$\therefore \vec{r}_i = \vec{0}$ for some $i \leq n$.

$\therefore A\vec{x}_i - \vec{b} = \vec{0}$ for some $i \leq n$.

$\therefore \vec{x}_i = \text{sol of } A\vec{x} = \vec{b}$ for some $i \leq n$.

Conjugate gradient method (Solve: $A\vec{x} = \vec{b}$)

Given $\vec{x}_0 \in \mathbb{R}^n$, $\vec{p}_0 = -\vec{r}_0 \stackrel{\text{def}}{=} -(A\vec{x}_0 - \vec{b})$, find \vec{x}_k and \vec{p}_k ($k=1, 2, \dots$) such that:

$$(a) \quad \vec{x}_{k+1} = \vec{x}_k + \alpha_k \vec{p}_k$$

$$(b) \quad \alpha_k = - \frac{\vec{r}_k \cdot \vec{p}_k}{\langle \vec{p}_k, \vec{p}_k \rangle_A} \quad \begin{aligned} \vec{r}_k &= A\vec{x}_k - \vec{b} \\ \langle \vec{u}, \vec{v} \rangle_A &= \vec{u} \cdot A\vec{v} \end{aligned}$$

$$(c) \quad \vec{p}_{k+1} = -\vec{r}_{k+1} - \beta_k \vec{p}_k$$

$$(d) \quad \beta_k = - \frac{\langle \vec{r}_{k+1}, \vec{p}_k \rangle_A}{\langle \vec{p}_k, \vec{p}_k \rangle_A}$$

Iteration converges in less than n iterations.
($\vec{r}_i \cdot \vec{r}_j = 0 \quad \forall i \neq j$)

Theorem: In the conjugate gradient method,

(i) $\vec{r}_i \cdot \vec{r}_j = 0$ for $i \neq j$

(ii) $\langle \vec{p}_i, \vec{p}_j \rangle_A \stackrel{\text{def}}{=} \vec{p}_i \cdot A \vec{p}_j = 0$ for $i \neq j$.

Lemma: $\text{Span} \{ \vec{p}_0, \dots, \vec{p}_{k-1} \} = \text{Span} \{ \vec{r}_0, \dots, \vec{r}_{k-1} \}$
 $= \text{Span} \{ \vec{r}_0, A \vec{r}_0, \dots, A^{k-1} \vec{r}_0 \}$

Proof: (i) and (ii) are true for $i, j \leq 1$

($\vec{r}_0 \cdot \vec{r}_1 = 0$ because $0 = \frac{d}{d\alpha} \Big|_{\alpha=\alpha_0} \varphi(\vec{x}_0 + \alpha \vec{p}_0) = \frac{\nabla \varphi(\vec{x}_0 + \alpha_0 \vec{p}_0)}{(A \vec{x}_1 - \vec{b})} \cdot \vec{p}_0$)

\vec{x}_1
 \vec{r}_1

$-\vec{r}_0$ $-\vec{r}_0$

$\langle \vec{p}_1, \vec{p}_0 \rangle_A = 0$ follows from the definition)

Suppose the statement is true for $i, j \leq k$. For $k+1$,

$$\because \text{Span} \{ \vec{p}_0, \dots, \vec{p}_j \} = \text{Span} \{ \vec{r}_0, \dots, \vec{r}_j \}$$

$$\therefore \text{we get } \vec{r}_k \cdot \vec{p}_j = 0 \text{ for } j=0, 1, 2, \dots, k-1 \text{ (By induction hypothesis)}$$

$\vec{r}_k \in \text{Span} \{ \vec{r}_0, \dots, \vec{r}_j \}$

Now, $\vec{r}_{k+1} = \vec{r}_k + \alpha_k A \vec{p}_k$

$$\left(\because \begin{pmatrix} A \vec{x}_{k+1} \\ -\vec{b} \end{pmatrix} = \begin{pmatrix} A \vec{x}_k \\ -\vec{b} \end{pmatrix} + \alpha_k A \vec{p}_k \right)$$

$$\Rightarrow \vec{r}_{k+1} \cdot \vec{p}_j = \vec{r}_k \cdot \vec{p}_j + \alpha_k \underbrace{A \vec{p}_k \cdot \vec{p}_j}_{\langle \vec{p}_k, \vec{p}_j \rangle_A} = 0 \text{ for } j=0, 1, 2, \dots, k-1$$

0 (induction hypothesis)

Also,

$$0 = \frac{d}{d\alpha} \Big|_{\alpha=\alpha_k} \varphi(\vec{x}_k + \alpha \vec{p}_k) = \underbrace{\nabla \varphi(\vec{x}_k + \alpha \vec{p}_k)}_{\begin{pmatrix} A \vec{x}_{k+1} \\ -\vec{b} \end{pmatrix} \cdot \vec{r}_{k+1}} \cdot \vec{p}_k$$

All together, we get $\vec{r}_{k+1} \cdot \vec{p}_j = 0$ for $j=0, 1, 2, \dots, k$

$$\therefore \text{Span}\{\vec{p}_0, \dots, \vec{p}_k\} = \text{Span}\{\vec{r}_0, \dots, \vec{r}_k\}$$

$$\therefore \vec{r}_{k+1} \cdot \vec{r}_j = 0 \text{ for } j=0, 1, 2, \dots, k$$

\therefore (i) is true for the case $k+1$.

To show (ii) for the case $k+1$ (given the induction hypothesis),

note that: $\vec{r}_{j+1} = \vec{r}_j + \alpha_j A\vec{p}_j \Rightarrow A\vec{p}_j \in \text{Span}\{\vec{r}_j, \vec{r}_{j+1}\}$

$$\therefore \vec{r}_{k+1} \cdot A\vec{p}_j = \langle \vec{r}_{k+1}, \vec{p}_j \rangle_A = 0 \text{ for } j=0, 1, 2, \dots, k-1$$

\uparrow
 $\text{Span}\{\vec{r}_j, \vec{r}_{j+1}\}$

$$\text{Now, } \vec{p}_{k+1} \cdot A \vec{p}_j = -\vec{r}_{k+1} \cdot A \vec{p}_j - \beta_k \vec{p}_k \cdot A \vec{p}_j$$

$$\langle \vec{p}_{k+1}, \vec{p}_j \rangle_A = 0 \quad \text{for } j=0, 1, 2, \dots, k-1$$

Also, $\langle \vec{p}_{k+1}, \vec{p}_k \rangle_A = 0$ by definition.

$$\therefore \langle \vec{p}_{k+1}, \vec{p}_j \rangle_A = 0 \quad \text{for } j=0, 1, 2, \dots, k$$

$$\therefore \langle \vec{p}_i, \vec{p}_j \rangle_A = 0 \quad \text{for } i, j \leq k+1.$$

By M.I., the theorem is generally true!!

$$\therefore \vec{r}_{k+1} \cdot \vec{p}_j = 0 \text{ for } j=0, 1, 2, \dots, k+1, k$$

$$\therefore \text{Span} \{ \vec{p}_0, \dots, \vec{p}_k \} = \text{Span} \{ \vec{r}_0, \dots, \vec{r}_k \}$$

$$\therefore \vec{r}_{k+1} \cdot \vec{r}_j = 0 \text{ for } j=0, 1, 2, \dots, k$$

$$\text{Span} \{ \vec{p}_0, \dots, \vec{p}_k \}$$

\therefore (i) is true for the case $k+1$.

To show (ii) for the row $k+1$ (given the induction hypothesis)

Note that: $\vec{r}_{j+1} = \vec{r}_j + \alpha_j A \vec{p}_j \Rightarrow A \vec{p}_j \in \text{Span}\{\vec{r}_j, \vec{r}_{j+1}\}$

$$\therefore \vec{r}_{k+1} \cdot A \vec{p}_j = \langle \vec{r}_{k+1}, \vec{p}_j \rangle_A = 0 \text{ for } j=0, 1, 2, \dots, k-1$$

$\text{Span}\{\vec{r}_j, \vec{r}_{j+1}\}$

$$\therefore \langle \vec{r}_{k+1}, \vec{p}_j \rangle_A = 0 \text{ for } j=0, 1, 2, \dots, k-1$$

induction hypothesis

$$\text{Now, } \vec{p}_{k+1} \cdot A \vec{p}_j = -\vec{r}_{k+1} \cdot A \vec{p}_j - \beta_k \vec{p}_k \cdot A \vec{p}_j = 0$$

$$\text{for } j=0, 1, 2, \dots, k-1 \quad (\vec{p}_{k+1} = -\vec{r}_{k+1} - \beta_k \vec{p}_k)$$

$$\therefore \langle \vec{p}_{k+1}, \vec{p}_j \rangle_A = 0 \text{ for } j=0, 1, 2, \dots, k-1$$

Also, $\langle \vec{p}_{k+1}, \vec{p}_k \rangle_A = 0$ (by definition)

All together,

$$\langle \vec{p}_{k+1}, \vec{p}_j \rangle_A = 0 \quad \text{for } j=0, 1, 2, \dots, k.$$

By M.I., the thn is true!!