

Conjugate gradient method

$$A \vec{x} = \vec{b} \quad A \text{ sym. posdef.} \quad q(\vec{x}) = \langle A \vec{x}, \vec{x} \rangle - 2 \langle \vec{b}, \vec{x} \rangle$$

$$\vec{x}^{(k+1)} = \vec{x}^{(k)} + t_k \vec{v}^{(k)} \quad \text{where } t_k = \frac{\langle \vec{v}^{(k)}, \vec{r}^{(k)} \rangle}{\langle \vec{v}^{(k)}, A \vec{v}^{(k)} \rangle}$$

↑
search direction

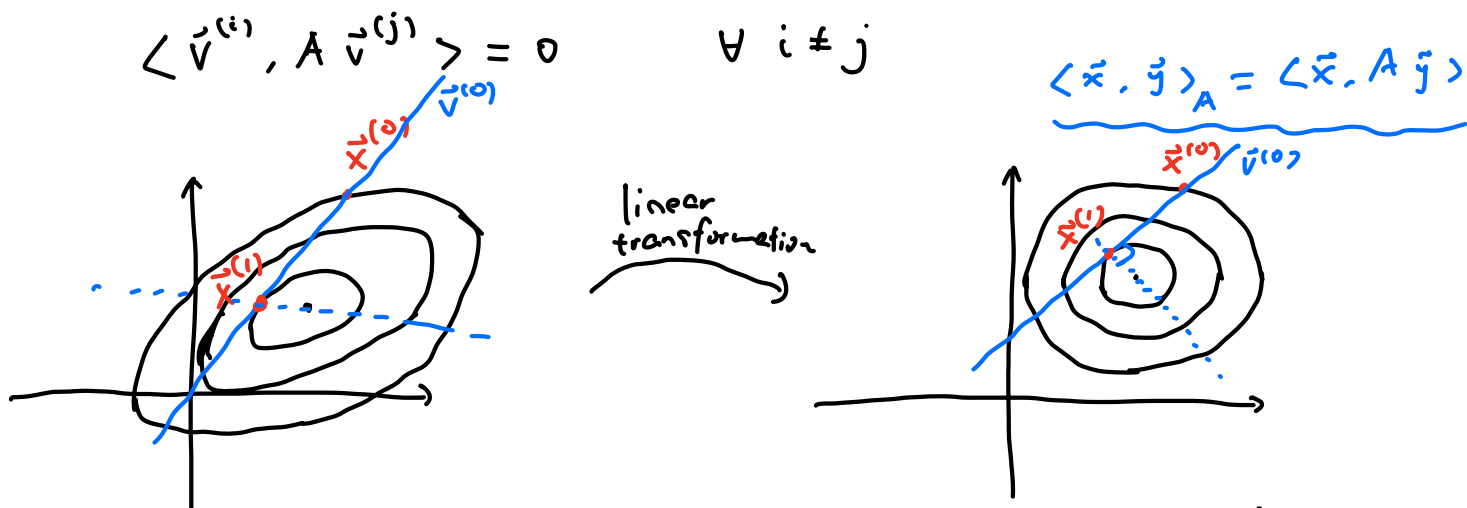
$$\vec{r}^{(k)} = \vec{b} - A \vec{x}^{(k)}$$

In Steepest descent, $\vec{v}^{(k)} = \vec{r}^{(k)}$

- It is desired for the search directions to have A-orthogonality, i.e.,

$$\langle \vec{v}^{(i)}, A \vec{v}^{(j)} \rangle = 0 \quad \forall i \neq j$$

$$\langle \vec{x}, \vec{y} \rangle_A = \langle \vec{x}, A \vec{y} \rangle$$



Such a method is called a conjugate direction method

Thm A conjugate direction method gets the exact sol'n to $A \vec{x} = \vec{b}$ within n iterations, i.e., for any $\vec{x}^{(0)}$, we have $A \vec{x}^{(n)} = \vec{b}$

Proof By normalization, we may assume $\langle \vec{v}^{(i)}, A \vec{v}^{(i)} \rangle = 1$.

$$\text{Then } \vec{x}^{(k+1)} = \vec{x}^{(k)} + t_k \vec{v}^{(k)} \quad \text{where } t_k = \langle \vec{v}^{(k)}, \vec{r}^{(k)} \rangle$$

$$\vec{x}^{(n)} = \vec{x}^{(0)} + t_0 \vec{v}^{(0)} + t_1 \vec{v}^{(1)} + \dots + t_{n-1} \vec{v}^{(n-1)}$$

$$A \vec{x}^{(n)} - \vec{b} = A(\vec{x}^{(0)} + t_0 \vec{v}^{(0)} + t_1 \vec{v}^{(1)} + \dots + t_{n-1} \vec{v}^{(n-1)}) - \vec{b}$$

For any $k = 0, \dots, n-1$,

$$\begin{aligned} \langle A \vec{x}^{(n)} - \vec{b}, \vec{v}^{(k)} \rangle &= \langle A \vec{x}^{(0)} - \vec{b}, \vec{v}^{(k)} \rangle + t_0 \langle A \vec{v}^{(0)}, \vec{v}^{(k)} \rangle \\ &\quad + \dots + t_{n-1} \langle A \vec{v}^{(n-1)}, \vec{v}^{(k)} \rangle \\ &= \langle A \vec{x}^{(0)} - \vec{b}, \vec{v}^{(k)} \rangle + t_k \end{aligned}$$

$$t_k = \langle \vec{b} - A \vec{x}^{(k)}, \vec{v}^{(k)} \rangle$$

$$= \langle \vec{b} - A(\vec{x}^{(0)} + t_0 \vec{v}^{(0)} + \dots + t_{k-1} \vec{v}^{(k-1)}), \vec{v}^{(k)} \rangle$$

$$= \langle \vec{b} - A \vec{x}^{(0)}, \vec{v}^{(k)} \rangle$$

$$\Rightarrow \langle A \vec{x}^{(n)} - \vec{b}, \vec{v}^{(k)} \rangle = 0 \quad k = 0, \dots, n-1$$

$$\Rightarrow A \vec{x}^{(n)} - \vec{b} = \vec{0}$$

Question: how to make search directions A -orthogonal?

$$\vec{w}^{(0)}, \vec{w}^{(1)}, \dots, \vec{w}^{(n-1)}$$

↓ Gram-Schmidt

$$\vec{v}^{(0)} = \vec{w}^{(0)}$$

$$\vec{v}^{(1)} = \vec{w}^{(1)} - \frac{\langle \vec{w}^{(1)}, \vec{v}^{(0)} \rangle_A}{\langle \vec{v}^{(0)}, \vec{v}^{(0)} \rangle_A} \vec{v}^{(0)}$$

$$\vec{v}^{(2)} = \vec{w}^{(2)} - \frac{\dots}{\dots} \vec{v}^{(0)} - \frac{\dots}{\dots} \vec{v}^{(1)}$$

...

too expensive!

- Key observation: if every time we take $\vec{r}^{(k)}$ and do Gram-Schmidt to make it A -orthogonal to $\vec{v}^{(0)}, \dots, \vec{v}^{(k-1)}$ and get $\vec{v}^{(k)}$, then $\vec{r}^{(k)}$ is already A -orthogonal to $\vec{v}^{(0)}, \dots, \vec{v}^{(k-2)}$ so G-S is simplified.

Proof ① $\text{Span} \{ \vec{v}^{(0)}, \dots, \vec{v}^{(k-1)} \} = \text{Span} \{ \vec{r}^{(0)}, \dots, \vec{r}^{(k-1)} \} = \mathcal{D}^{(k)}$

② $\langle \vec{r}^{(k)}, \vec{v}^{(i)} \rangle = 0 \quad i = 0, \dots, k-1 \quad \Rightarrow \langle \vec{r}^{(k)}, \vec{r}^{(i)} \rangle = 0 \quad \forall i \neq k$

$$\langle \vec{r}^{(k)}, \vec{v}^{(i)} \rangle = \langle \vec{b} - A \vec{x}^{(k)}, \vec{v}^{(i)} \rangle$$

$$= \langle \vec{b} - A (\underbrace{\vec{x}^{(0)} + t_0 \vec{v}^{(0)} + \dots + t_{i-1} \vec{v}^{(i-1)}}_{\vec{x}^{(i)}} + t_i \vec{v}^{(i)} + \dots$$

$$+ t_{k-1} \vec{v}^{(k-1)}) , \vec{v}^{(i)} \rangle$$

$$= \langle \vec{b} - A \vec{x}^{(i)}, \vec{v}^{(i)} \rangle - t_i \langle A \vec{v}^{(i)}, \vec{v}^{(i)} \rangle$$

$$= \langle \vec{r}^{(i)}, \vec{v}^{(i)} \rangle - t_i \langle A \vec{v}^{(i)}, \vec{v}^{(i)} \rangle = 0$$

$$\text{Since } t_i = \frac{\langle \vec{r}^{(i)}, \vec{v}^{(i)} \rangle}{\langle A \vec{v}^{(i)}, \vec{v}^{(i)} \rangle}$$

$$\textcircled{3} \quad \vec{r}^{(k-1)} - \vec{r}^{(k-2)} = (\vec{b} - A \vec{x}^{(k-1)}) - (\vec{b} - A \vec{x}^{(k-2)})$$

$$= -A(\vec{x}^{(k-1)} - \vec{x}^{(k-2)}) = -t_{k-2} A \vec{v}^{(k-2)}$$

$$\vec{r}^{(k-2)} - \vec{r}^{(k-3)} = -t_{k-3} A \vec{v}^{(k-3)}$$

⋮

$$\vec{r}^{(1)} - \vec{r}^{(0)} = -t_0 A \vec{v}^{(0)}$$

any $t_i \neq 0$

$$\Rightarrow A D^{(k-1)} \subset D^{(k)} \quad \text{"Krylov subspaces"}$$

Finally, $\textcircled{2}$ gives that $\vec{r}^{(k)}$ is orthogonal to $D^{(k)}$, i.e.,

$$\langle \vec{r}^{(k)}, \vec{x} \rangle = 0 \quad \forall \vec{x} \in D^{(k)}$$

Then, $\forall \vec{y} \in D^{(k-1)}$, $\textcircled{3}$ gives $A \vec{y} \in D^{(k)}$

$$\Rightarrow \langle \vec{r}^{(k)}, A \vec{y} \rangle = 0$$

Since $D^{(k-1)} = \text{Span} \{ \vec{v}^{(0)}, \dots, \vec{v}^{(k-2)} \}$, we get

$\vec{r}^{(k)}$ is A -orthogonal to $\vec{v}^{(0)}, \dots, \vec{v}^{(k-2)}$.

This gives the Conjugate gradient method:

$$\vec{v}^{(k)} = \vec{r}^{(k)} - \frac{\langle \vec{r}^{(k)}, A \vec{v}^{(k-1)} \rangle}{\langle \vec{v}^{(k-1)}, A \vec{v}^{(k-1)} \rangle} \vec{v}^{(k-1)} \quad k=1, 2, \dots$$

$$\vec{v}^{(0)} = \vec{r}^{(0)}$$

Simplify: ① $\vec{r}^{(k)} - \vec{r}^{(k-1)} = -t_{k-1} A \vec{v}^{(k-1)}$

$$\langle \vec{r}^{(k)}, \vec{r}^{(k)} \rangle - \langle \vec{r}^{(k-1)}, \vec{r}^{(k)} \rangle = -t_{k-1} \langle A \vec{v}^{(k-1)}, \vec{r}^{(k)} \rangle$$

$$\Rightarrow \langle A \vec{v}^{(k-1)}, \vec{r}^{(k)} \rangle = -\frac{1}{t_{k-1}} \langle \vec{r}^{(k)}, \vec{r}^{(k)} \rangle$$

② $\langle \vec{r}^{(k)}, \vec{v}^{(k-1)} \rangle - \langle \vec{r}^{(k-1)}, \vec{v}^{(k-1)} \rangle = -t_{k-1} \langle A \vec{v}^{(k-1)}, \vec{v}^{(k-1)} \rangle$

$$\Rightarrow \langle A \vec{v}^{(k-1)}, \vec{v}^{(k-1)} \rangle = \frac{1}{t_{k-1}} \langle \vec{r}^{(k-1)}, \vec{v}^{(k-1)} \rangle$$

$$= \frac{1}{t_{k-1}} \langle \vec{r}^{(k-1)}, \vec{r}^{(k-1)} \rangle$$

$$\vec{v}^{(k-1)} = \vec{r}^{(k-1)} + \dots + \vec{v}^{(k-2)}$$

⇒ Simplified version:

$$\vec{v}^{(k)} = \vec{r}^{(k)} + \frac{\langle \vec{r}^{(k)}, \vec{r}^{(k)} \rangle}{\langle \vec{r}^{(k-1)}, \vec{r}^{(k-1)} \rangle} \vec{v}^{(k-1)}$$

- The n -step termination property is not achieved in reality due to round-off errors. However, Conjugate gradient method is a good iterative method (one stops before step n to get an approximate sol'n).
- Error estimate $\|\vec{e}^{(k)}\|_A \leq 2 \left(\frac{\sqrt{\kappa(A)} - 1}{\sqrt{\kappa(A)} + 1} \right)^k \|\vec{e}^{(0)}\|_A$ $\|\vec{x}\|_A := \sqrt{\langle \vec{x}, A \vec{x} \rangle}$
- For a general system $A \vec{x} = \vec{b}$, one can solve the normal equation

$$\underbrace{A^T A}_{\text{sym. posdef.}} \vec{x} = A \vec{b}$$

sym. posdef.

and Conjugate gradient applies.

However, this makes condition number worse :

$$\kappa(A^T A) = \kappa(A)^2$$