

Notes for Wednesday, March 25

Nocedal & Wright p. 103 claim

if $x_{k+1} = x_k + \alpha p_k$

the $\alpha \in R$ that minimizes $\phi(x_k + \alpha p_k)$ over $\alpha \in R$ is

$$\alpha_k = \frac{-r_k^T p_k}{p_k^T A p_k}$$

To see this, recall

$$\phi(x) = \frac{1}{2} x^T A x - b^T x \quad (A \text{ SPD})$$

$$\begin{aligned} \therefore \phi(x_k + \alpha p_k) &= \frac{1}{2} (x_k + \alpha p_k)^T A (x_k + \alpha p_k) - b^T (x_k + \alpha p_k) \\ &= \frac{1}{2} x_k^T A x_k + \alpha x_k^T A p_k + \frac{1}{2} \alpha^2 p_k^T A p_k \\ &\quad - b^T x_k - \alpha b^T p_k \end{aligned}$$

$$\begin{aligned} \therefore \frac{d}{d\alpha} \phi(x_k + \alpha p_k) &= x_k^T A p_k + \alpha p_k^T A p_k - b^T p_k \\ &= (A x_k - b)^T p_k + \alpha p_k^T A p_k \\ &= r_k^T p_k + \alpha p_k^T A p_k \end{aligned}$$

$$\therefore \frac{d}{d\alpha} \phi(x_k + \alpha p_k) = 0$$

$$\Leftrightarrow \alpha = \frac{-r_k^T p_k}{p_k^T A p_k}$$

Proof of Theorem 5.1

also $p_i \neq 0 \forall i$

N + W say the conjugate directions $\{p_0, p_1, \dots, p_{n-1}\}$

satisfying $p_i^T A p_j = 0$ for $i \neq j$

are linearly independent.

Why?

To show that $\{p_0, p_1, \dots, p_{n-1}\}$ are linearly ind. in R^n

need to show that if $\sum_{j=0}^{n-1} \alpha_j p_j = 0$

then all $\alpha_i = 0$.

So suppose $\sum_{j=0}^{n-1} \alpha_j p_j = 0$.

$$\text{Then } 0 = p_i^T A \left(\sum_{j=0}^{n-1} \alpha_j p_j \right)$$

$$= \sum_{j=0}^{n-1} \alpha_j p_i^T A p_j$$

$$= \alpha_i p_i^T A p_i \quad (\text{because } p_i^T A p_j = 0 \text{ for } i \neq j)$$

Since $p_i^T A p_i > 0$ (because A is SPD and $p_i \neq 0$)

must have $\alpha_i = 0$. This argument holds for all $i = 0, 1, \dots, n-1$.

So $\alpha_i = 0$ for all $i = 0, 1, 2, \dots, n-1$.

Bottom of p. 105

New claim

$S^T A S$ is diagonal

where $S = [p_0, p_1, \dots, p_{n-1}]$

and $p_i^T A p_j = 0$ for $i \neq j$.

Why?

$$S^T A S = \begin{bmatrix} p_0^T \\ p_1^T \\ \vdots \\ p_{n-1}^T \end{bmatrix} A [p_0, p_1, \dots, p_{n-1}]$$

$$= \begin{bmatrix} p_0^T \\ p_1^T \\ \vdots \\ p_{n-1}^T \end{bmatrix} [A p_0, A p_1, \dots, A p_{n-1}]$$

So the (i, j) element of $S^T A S$ is

$$p_i^T (A p_j) = p_i^T A p_j = 0 \text{ if } i \neq j.$$

(4)

If A is diagonal, $A = \begin{pmatrix} d_1 & 0 & 0 & \dots & 0 \\ 0 & d_2 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & \dots & d_n \end{pmatrix}$

then the co-ordinate directions $e_i = \begin{pmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{pmatrix} \leftarrow i$

are conjugate.

$$e_i^T A e_j = e_i^T (A e_j) = (0 \dots 0 \underset{\uparrow i}{1} 0 \dots 0) \begin{pmatrix} 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \end{pmatrix} \leftarrow j$$

$$= 0$$

(S.10) $r_{k+1} = r_k + \alpha_k A p_k$

why?

Recall $r_k = A x_k - b$ and $x_{k+1} = x_k + \alpha_k p_k$

$$\begin{aligned} \therefore r_{k+1} &= A x_{k+1} - b \\ &= A (x_k + \alpha_k p_k) - b \\ &= A x_k + \alpha_k A p_k - b \\ &= A x_k - b + \alpha_k A p_k \\ &= r_k + \alpha_k A p_k \end{aligned}$$

N + W p. 106

$$h(\sigma) = \phi(x_0 + \sigma_0 p_0 + \dots + \sigma_{k-1} p_{k-1})$$

is a strictly convex quadratic (in the $\sigma_0, \dots, \sigma_{k-1}$)

First note that $h(\sigma)$ is a quadratic in $\sigma_0, \dots, \sigma_{k-1}$.

$$\begin{aligned}
h(\sigma) &= \phi(x_0 + \sigma_0 p_0 + \dots + \sigma_{k-1} p_{k-1}) \\
&= \frac{1}{2} (x_0 + \sigma_0 p_0 + \dots + \sigma_{k-1} p_{k-1})^T A (x_0 + \sigma_0 p_0 + \dots + \sigma_{k-1} p_{k-1}) \\
&\quad - b^T (x_0 + \sigma_0 p_0 + \dots + \sigma_{k-1} p_{k-1}) \\
&= \frac{1}{2} x_0^T A x_0 + x_0^T A (\sigma_0 p_0 + \dots + \sigma_{k-1} p_{k-1}) \\
&\quad + \frac{1}{2} (\sigma_0 p_0 + \dots + \sigma_{k-1} p_{k-1})^T A (\sigma_0 p_0 + \dots + \sigma_{k-1} p_{k-1}) \\
&\quad - b^T x_0 - b^T (\sigma_0 p_0 + \dots + \sigma_{k-1} p_{k-1}) \\
&= \frac{1}{2} x_0^T A x_0 + \sigma_0 x_0^T A p_0 + \dots + \sigma_{k-1} x_0^T A p_{k-1} \\
&\quad + \frac{1}{2} \sigma_0^2 p_0^T A p_0 + \dots + \frac{1}{2} \sigma_{k-1}^2 p_{k-1}^T A p_{k-1} \\
&\quad - b^T x_0 - \sigma_0 b^T p_0 - \sigma_{k-1} b^T p_{k-1}
\end{aligned}$$

(Note all the terms $\frac{1}{2} \sigma_i \sigma_j p_i^T A p_j = 0$ for $i \neq j$ because $\{p_i\}$ conjugate)

$\therefore h(\sigma)$ is a quadratic in the σ_i

(6)

To see the $h(\sigma)$ is strictly convex,

consider its Hessian matrix $H(\sigma) = \left(\frac{\partial^2 h(\sigma)}{\partial \sigma_i \partial \sigma_j} \right)$

$$H \frac{\partial h(\sigma)}{\partial \sigma_j} = x_0^T A p_j + \sigma_j p_j^T A p_j - b^T p_j$$

$$\therefore \frac{\partial^2 h(\sigma)}{\partial x_i \partial x_j} = \begin{cases} p_i^T A p_i & \text{if } i=j \\ 0 & \text{if } i \neq j \end{cases}$$

Note also $p_i^T A p_i > 0$ since A SPD and $p_i \neq 0$.

$\therefore H(\sigma)$ is a diagonal matrix with positive diagonal elements

$\Rightarrow H(\sigma)$ is symmetric positive-definite

$\Rightarrow h(\sigma)$ is strictly convex.

(7)

Proof of Theorem 5.2 N&W p. 106

$h(\sigma)$ strictly convex so has a unique minimizer σ^* that satisfies

$$\frac{\partial h(\sigma^*)}{\partial \sigma_i} = 0 \quad i=0, 1, \dots, k-1 \quad (1)$$

$$h(\sigma) = \varphi(x_0 + \sigma_0 p_0 + \dots + \sigma_{k-1} p_{k-1})$$

$$\text{So } \frac{\partial h(\sigma)}{\partial \sigma_i} = \nabla \varphi(x_0 + \sigma_0 p_0 + \dots + \sigma_{k-1} p_{k-1})^T p_i$$

Therefore (1) is equivalent to

$$\nabla \varphi(x_0 + \sigma_0^* p_0 + \dots + \sigma_{k-1}^* p_{k-1})^T p_i = 0 \quad \text{for } i=0, 1, \dots, k-1 \quad (2)$$

However, recall for $\varphi(x) = \frac{1}{2} x^T A x - b^T x$

$$\nabla \varphi(x) = Ax - b = r(x)$$

∴ (2) is equivalent to

$$r(\tilde{x})^T p_i = 0 \quad \text{for } i=0, 1, \dots, k-1$$

$$\text{where } \tilde{x} = x_0 + \sigma_0^* p_0 + \dots + \sigma_{k-1}^* p_{k-1}$$

Bottom of p. 106 of N+W. Claim

$$r_1^T p_0 = 0$$

Note $r_1 = Ax_1 - b$ and $x_1 = x_0 + \alpha_0 p_0$

$$\alpha_0 = - \frac{r_0^T p_0}{p_0^T A p_0} \quad (\text{see (5.7) in N+W})$$

$$\begin{aligned} \therefore r_1^T p_0 &= (Ax_1 - b)^T p_0 \\ &= (A(x_0 + \alpha_0 p_0) - b)^T p_0 \\ &= (Ax_0 - b + \alpha_0 A p_0)^T p_0 \\ &= (r_0 + \alpha_0 A p_0)^T p_0 \\ &= r_0^T p_0 + \alpha_0 p_0^T A p_0 \\ &= r_0^T p_0 - \frac{r_0^T p_0}{p_0^T A p_0} p_0^T A p_0 \\ &= 0 \end{aligned}$$

N&W p. 107

Eigen vectors satisfy conjugacy property

A SPD $\Rightarrow \exists$ an orthogonal matrix Q s.t.
(i.e. $Q Q^T = Q^T Q = I$)

$$Q^T A Q = \Lambda = \begin{pmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & & 0 \\ \vdots & & \ddots & \\ 0 & \dots & 0 & \lambda_n \end{pmatrix} \quad (1)$$

Let $Q = [z_1, z_2 \dots z_n]$

(1) is equivalent to

$$A Q = Q \Lambda$$

j^{th} column of $A Q$ is $A z_j$ and

j^{th} column of $Q \Lambda$ is $\lambda_j z_j$

So (1) $\Rightarrow A z_j = \lambda_j z_j$

\Rightarrow the matrix Q consists of eigenvectors of A that are normalized so that

$$z_i^T z_j = \begin{cases} 1 & \text{if } i=j \\ 0 & \text{if } i \neq j \end{cases}$$

(This comes from $Q^T Q = I$)

$$\Rightarrow \begin{bmatrix} z_1^T \\ \vdots \\ z_n^T \end{bmatrix} [z_1, z_2 \dots z_n] = I$$

(10)

\Rightarrow (i, j) element of $Q^T Q$ is $z_i^T z_j$

and (i, j) element of I is $\begin{cases} 1 & \text{if } i=j \\ 0 & \text{if } i \neq j \end{cases}$

For these normalized eigenvectors in the Q matrix

$$\begin{aligned} z_i^T A z_j &= z_i^T (A z_j) = z_i^T (\lambda_j z_j) = \lambda_j z_i^T z_j \\ &= \begin{cases} \lambda_j & \text{if } i=j \\ 0 & \text{if } i \neq j \end{cases} \end{aligned}$$

\therefore The set of eigenvectors from Q

$$\{z_1, z_2, \dots, z_n\}$$

is a set of conjugate vectors for A

Note not all eigenvectors are conjugate.

E.g. suppose $A = I$

Then $z_1 = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$ and $z_2 = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$ are both

eigenvectors of I since $I z_1 = z_1$ & $I z_2 = z_2$

But $z_1^T I z_2 = z_1^T z_2 = 1 \Rightarrow$ not conjugate.

This can only occur when A has eigenvalues $\lambda_i = \lambda_j$ for some $i \neq j$.