

## Conjugate Gradients

Positive Definite  $A = A'$ . To solve  $Az = b$  for  $z = A^{-1}b$ , choose  $x_{-1} := x_0$  arbitrarily and, for  $n = 0, 1, 2, 3, \dots$  in turn, compute  $x_{n+1} := x_n + \beta_n \cdot (b - Ax_n) + \mu_n \cdot (x_n - x_{n-1})$  with scalars  $\beta_n$  and  $\mu_n$  chosen to minimize  $(x_{n+1} - z)'A(x_{n+1} - z) = x_{n+1}' \cdot Ax_{n+1} - 2b'x_{n+1} + z'Az$ . Simplify typography by dropping subscripts from  $r_n := b - Ax_n$ ,  $d_n := x_n - x_{n-1}$ ,  $\beta_n$  and  $\mu_n$  to find that

$$[r, d]'A[r, d] \begin{bmatrix} \beta \\ \mu \end{bmatrix} = \begin{bmatrix} r'Ar & r'Ad \\ d'Ar & d'Ad \end{bmatrix} \begin{bmatrix} \beta \\ \mu \end{bmatrix} = \begin{bmatrix} r'r \\ d'r \end{bmatrix} = [r, d]'r.$$

Solve this equation for  $\beta$  and  $\mu$ . At least one solution always exists if  $A$  is positive definite.

In the absence of roundoff, successive residuals  $r_n := b - Ax_n$  turn out to be orthogonal; in fact

$$r_m'r_n = 0 = d_m'Ad_n \quad \text{for all } m > n \geq 0.$$

Consequently  $r_m = 0$  and  $x_m = z$  at least as soon as  $m$  equals the dimension of  $A$ . But the point of the iteration is *not* to iterate that many times when the dimension is huge. Instead, take advantage of the tendency of residuals  $r_n$  and increments  $d_n$  to dwindle as  $n$  increases, and stop iterating when they both become small enough.

## Overrelaxation

Positive Definite  $A = A' = -L + V - L'$  in which  $V := \text{Diag}(A) = V'$  is Positive Definite too, and  $-L = \text{Subdiag}(A)$ . Given  $A$  and  $b$  we seek  $z := A^{-1}b$ . Starting from an arbitrary initial guess  $x_0$ , for  $n = 0, 1, 2, 3, \dots$  in turn, ordinary Gauss-Seidel iteration solves

$V(x_{n+1} - x_n) = b + Lx_{n+1} - Vx_n + L'x_n$  for  $x_{n+1} = (V - L)^{-1}(b + L'x_n)$ . Then  $(x_{n+1} - z) = E(x_n - z)$  where  $E = (V - L)^{-1}L'$  can be shown to have eigenvalues all with magnitudes less than 1, though not necessarily much less unless  $\|L\|$  is rather smaller than the smallest eigenvalue of  $V$ .

To accelerate convergence, consider using an Over/Underrelaxation parameter  $\delta$  confined to  $-1 < \delta < 1$  for reasons to be explained later. To solve  $Az = b$  for  $z = A^{-1}b$ , choose  $x_0$  arbitrarily and, for  $n = 0, 1, 2, 3, \dots$  in turn, solve  $V(x_{n+1} - x_n) = (1 + \delta)(b + Lx_{n+1} - Vx_n + L'x_n)$  for  $x_{n+1} = (V - (1 + \delta)L)^{-1}(Vx_n + (1 + \delta)(b - Vx_n + L'x_n))$ . Then  $(x_{n+1} - z) = E(x_n - z)$  where  $E = (V - (1 + \delta)L)^{-1}(-\delta V + (1 + \delta)L')$ . Note that, because  $L$  lies strictly below the diagonal, (product of all  $E$ 's eigenvalues)  $= \det(E) = \det(-\delta I)$ . Therefore at least one eigenvalue of  $E$  has magnitude at least as big as  $|\delta|$ . This is why we keep  $-1 < \delta < 1$ .

$E$  and its eigenvalues depend upon  $\delta$ , as well as  $A$ , but the dependence is obscure except in special cases. An important special case arises when  $A = \begin{bmatrix} I & -B \\ -B & I \end{bmatrix}$ . In this case every eigenvalue  $\alpha$  of  $A$  has the form  $\alpha = 1 \pm \beta$  where  $\beta$  is either a singular value of  $B$  or, if  $B$  is not square, 0. And in this case every eigenvalue  $\varepsilon$  of  $E$  can be shown easily to satisfy  $(\varepsilon + \delta) = \pm \beta(1 + \delta)\sqrt{\varepsilon}$ ;

$$\varepsilon = ((1 + \delta)\beta/2 \pm \sqrt{((1 + \delta)\beta/2)^2 - \delta})^2.$$

The largest of the magnitudes of eigenvalues  $\varepsilon$  is minimized when  $\delta = (\|B\|/(1 + \sqrt{(1 - \|B\|^2)}))^2$ , and then every eigenvalue  $\varepsilon$  has the same magnitude  $\delta$ .