

# Conjugate Gradient Algorithm

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December 9, 2018

The values of parameter  $\lambda_0 = (\lambda_1, \lambda_2, \dots, \lambda_n)$  can be obtained by solving the following linear equation:

$$\Gamma_0 \lambda_0 = \gamma_0 \quad (1)$$

where  $\Gamma_0$  is a symmetric  $n \times n$  matrix,

$$[\Gamma_0]_{ij} = \gamma(x_i - x_j),$$

and

$$\gamma_0 = (\gamma(x_0 - x_1), \dots, \gamma(x_0 - x_n)).$$

Because the parameter  $\lambda_0$  is the solution of the linear system (eq. 1), we have  $\lambda_0 = \gamma_0^{-1} \gamma_0$ . **However, for large data sets, obtaining the inverse of  $\Gamma_0$  is generally difficult.** We propose here to minimize the function  $\phi(x)$ , defined by

$$\phi(x) = \frac{1}{2} X^T \Gamma_0 X - X^T \gamma_0 \quad (2)$$

The minimum value of  $\phi$  is  $-\gamma_0^T \Gamma_0^{-1} \gamma_0 / 2$ , obtained by setting  $x = \Gamma_0^{-1} \gamma_0$ . Thus, minimizing  $\phi$  and solving (eq. 2) are equivalent problems. The *conjugate gradient algorithm* is an iterative method used to minimize (eq. 2). If  $\Gamma_0$  is a  $n \times n$  matrix the conjugate gradient algorithm will converge in  $n$  iterations to the solution. This method considers the successive minimization of  $\phi$  along a set of directions  $\{p_1, p_2, \dots\}$ . If  $x_{k-1}$  is the current approximation to the solution in (eq. 2) for a direction  $p_k$ , then  $x_k = x_{k-1} + \alpha p_k$  will be the new conjugate gradient iterate, where we choose  $\alpha$  to minimize (eq. 2). It is easy to show that to minimize  $\phi(x_{k-1} + \alpha p_k)$  with respect to  $\alpha$ , we merely set

$$\alpha = \alpha_k = p_k^T (\gamma_0 - \Gamma_0 x_{k-1}) / p_k^T \Gamma_0 p_k.$$

The convergence rate of the algorithm will depend on the starting vector.