Minimization in \mathbb{R}^N : Gradient Methods

Let us consider a functional $\mathcal{J}(\mathbf{X}) : \mathbb{R}^N \mapsto \mathbb{R}$, defined as $\mathcal{J}(\mathbf{X}) = \frac{1}{2}\mathbf{X} \cdot \left[\underline{\mathcal{C}}\mathbf{X}\right] + \mathbf{B}_0 \cdot \mathbf{X}$, where $\underline{\mathcal{C}}$ is a $N \times N$ matrix and \mathbf{B}_0 is a vector of size N. For example

$$\underline{\mathcal{C}} = -(N+1) \begin{pmatrix} -2 & 1 & 0 & \cdots & 0 \\ 1 & -2 & 1 & \ddots & \vdots \\ 0 & \ddots & \ddots & \ddots & 0 \\ \vdots & \ddots & 1 & -2 & 1 \\ 0 & \cdots & 0 & 1 & -2 \end{pmatrix} \quad \text{and} \quad \underline{B}_0 = -\begin{pmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ (N+1) \end{pmatrix}$$

and in this case the minimum of \mathcal{J} is $U \in \mathbb{R}^N$ with $U_j = \frac{j}{N+1}$ In order to solve the minimization problem in \mathbb{R}^N it is defined, step by step from a gigen vector V^0 (for example $V^0 \equiv 0$), positions $V^k \in \mathbb{R}^N$ such as $\mathcal{J}(V^{k+1}) \leq \mathcal{J}(V^k)$

For the gradient methods

$$\boldsymbol{V}^{k+1} = \boldsymbol{V}^k + \alpha_k \boldsymbol{d}^k$$
 where $\boldsymbol{d}^k = -\nabla \mathcal{J}(\boldsymbol{V}^k)$.

In the curent case, the gradient can be computed either analiticaly or numerically.

- Gradient method with Constant step $\alpha_k = \alpha$. In a fortran program, compute V_{α}^K , for N = 200, K = N/2, using values $\alpha = 10, 1, 10^{-1}, 10^{-2}, ...$, For the defined example, plot $||\boldsymbol{U} \boldsymbol{V}_{\alpha}^K||$ as a function of α and define, in this case, an approximated convergence criteria.
- **Gradient method with optimal step.** For a given vector V_k and a descent direction $d_k \in \mathbb{R}^N$, we define a functional $f_k(\rho) : \mathbb{R} \mapsto \mathbb{R}$ as $f_k(\rho) = \mathcal{J}(V_k + \rho d_k)$ Then for the optimal step, α_k is the minimum of $f_k(\rho)$ on an interval [0, b] with 0 < b. In a fortran program, compute V_b^K , for N = 200, K = N/2, using values $b = 10^{-2}$, 10^{-1} , 1, 10^2 , 10^3 , ..., For the defined example, plot $||U V_b^K||$ as a function of b.
- **Gradient method with optimal step and equality constraint.** In this item we consider the minimization in a sub-space \mathcal{E} defined by vector \mathbf{O}_e the normal \mathbf{n} with $\|\mathbf{n}\| \neq 0$: $\mathcal{X} \in \mathcal{E} \iff (\mathcal{X} \mathbf{O}_e) \cdot \mathbf{n} = 0$. Propose a modification of the optimal step method to approximate the minimum of J on \mathcal{E} .
- **Gradient method with optimal step and inequality constraint.** In this item we consider the minimization in a half space \mathcal{E} defined by vector \mathbf{O}_e the normal \mathbf{n} with $\|\mathbf{n}\| \neq 0 : \mathcal{X} \in \mathcal{E} \iff (\mathcal{X} - \mathbf{O}_e) \cdot \mathbf{n} \ge 0$. Propose a modification of the optimal step method to approximate the minimum of J on \mathcal{E} .
- Gradient method with optimal step and strict inequality constraint. What about the case of \mathcal{E} defined by vector O_e the normal n with $||n|| \neq 0 : \mathcal{X} \in \mathcal{E} \iff (\mathcal{X} O_e) \cdot n > 0$?

for the minimization of $f_k(\rho)$ use the Dichotomous or the GoldSection algorithm.