

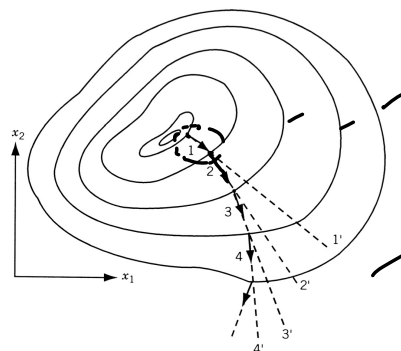
01-oct-2021

Indirect Search Methods. (Descent)

10

Gradient of an objective function.

$$\nabla f = \begin{Bmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{Bmatrix} \quad \nabla f = \begin{Bmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \end{Bmatrix}$$



If we move along the gradient direction, the value of the function increases at the fastest rate

however, the problem is that it is a local property

steepest Ascent direction : ∇f

steepest Descent " : $-\nabla f$

Arbitrary point \underline{x} in \mathbb{R}^n

f be the objective function value at \underline{x}

Consider a neighbouring point $\underline{x} + d\underline{x}$

$$d\underline{x} = \begin{Bmatrix} dx_1 \\ dx_2 \\ \vdots \\ dx_n \end{Bmatrix}$$

$$d\underline{x}^T d\underline{x} = (ds)^2$$

$$d\underline{x} = ds \underline{u} \quad \text{unit vector along } d\underline{x}$$

$f + df$ represents the value of the objective fu. @ $\underline{x} + d\underline{x}$

$$\begin{aligned} df &= \frac{\partial f}{\partial x_1} dx_1 + \frac{\partial f}{\partial x_2} dx_2 + \dots + \frac{\partial f}{\partial x_n} dx_n \\ &= \sum_{i=1}^n \left(\frac{\partial f}{\partial x_i} \right) dx_i = \nabla f^T d\underline{x} \end{aligned}$$

$$df = \nabla f^T d\tilde{x}$$

$$= d\beta \nabla f^T \tilde{u}$$

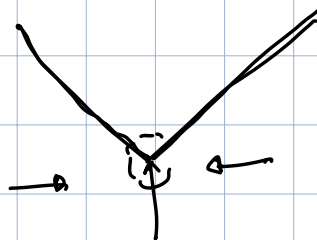
$$\therefore \boxed{\frac{df}{d\beta}} = \nabla f^T \tilde{u} = \|\nabla f\| \|\tilde{u}\| \cos \theta$$

The maximum variation of f w.r.t. β takes place when $\theta = 0 \Rightarrow \tilde{u}$ is in the ^{same} direction as ∇f

$$\boxed{\left. \frac{df}{d\beta} \right|_{\max} = \|\nabla f\|}$$

$$\left. \frac{\partial f}{\partial x_i} \right|_{x_m} \approx \frac{f(\underline{x}_m + \Delta x_i \underline{u}_i) - f(\underline{x}_m)}{\Delta x_i} \quad \text{f.d.}$$

$$\left. \frac{\partial f}{\partial x_i} \right|_{x_m} \approx \frac{f(\underline{x}_m + \Delta x_i \underline{u}_i) - f(\underline{x}_m - \Delta x_i \underline{u}_i)}{2 \Delta x_i}$$



Rate of change of a function along a direction.

$$\underline{x}_i \rightarrow \underline{x} = \underline{x}_i + \lambda \underline{s}_i \quad \checkmark$$

$$\frac{df}{d\lambda} = \sum_{j=1}^n \frac{\partial f}{\partial x_j} \frac{\partial x_j}{\partial \lambda}$$

$$\frac{\partial \pi_j}{\partial \lambda} = \frac{\partial}{\partial \lambda} (\pi_{ij} + \lambda s_{ij}) = \underline{s}_{ij}$$

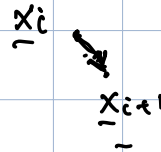
(16)

π_{ij} is the j th component of \underline{x}_i & s_{ij} is the j th component of \underline{s}_i

$$\frac{df}{d\lambda} = \sum_{j=1}^n \frac{\partial f}{\partial \pi_{ij}} s_{ij} = \nabla f^T \underline{s}_i$$

If λ^* minimizes f in the direction of \underline{s}_i

$$\left. \frac{df}{d\lambda} \right|_{\lambda=\lambda^*} = 0 \Rightarrow \nabla f^T \big|_{\underline{x}_i + \lambda^* \underline{s}_i} \underline{s}_i = 0$$

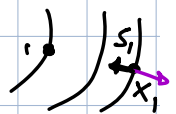


• Steepest Descent Method: (Cauchy)

1 start with initial guess \underline{x}_1 , $i=1$

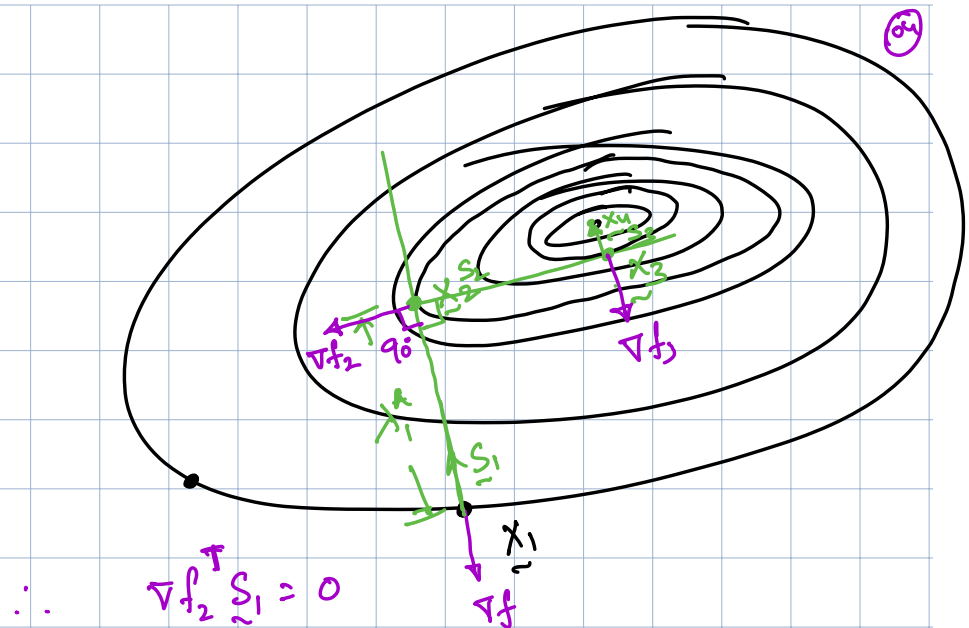
2 Find the search direction \underline{s}_i

$$\underline{s}_i = -\nabla f_i = -\nabla f(\underline{x}_i)$$



3
$$\underline{x}_{i+1} = \underline{x}_i + \lambda_i^* \underline{s}_i = \underline{x}_i - \lambda_i^* \nabla f_i$$

4 Check \underline{x}_{i+1} for optimality. If \underline{x}_{i+1} is not the optimum $i = i+1$, go to step 2



Minimize $f(x_1, x_2) = x_1 - x_2 + 2x_1^2 + 2x_1x_2 + x_2^2$
 from $\underline{x}_1 = \begin{Bmatrix} 0 \\ 0 \end{Bmatrix}$

$i=1 \quad \nabla f = \begin{Bmatrix} 1 + 4x_1 + 2x_2 \\ -1 + 2x_2 + 2x_1 \end{Bmatrix} \quad \checkmark$

$\nabla f|_1 = \begin{Bmatrix} 1 \\ -1 \end{Bmatrix} \quad S_1 = \begin{Bmatrix} -1 \\ 1 \end{Bmatrix}$

$\underline{x}_2 = \underline{x}_1 + \lambda_1 \underline{S}_1 = \begin{Bmatrix} 0 \\ 0 \end{Bmatrix} + \lambda_1 \begin{Bmatrix} -1 \\ 1 \end{Bmatrix} = \begin{Bmatrix} -\lambda_1 \\ \lambda_1 \end{Bmatrix} \quad \checkmark$

find λ_1^*

$\frac{df}{d\lambda_1} = 0 \Rightarrow f = -\lambda_1 - \lambda_1 + 2\cancel{\lambda_1} - 2\cancel{\lambda_1} + \lambda_1^2$

$\frac{df}{d\lambda_1} = -2 + 2\lambda_1 = 0 \Rightarrow \lambda_1^* = 1$

$$\therefore \underline{x}_2 = \begin{Bmatrix} -1 \\ 1 \end{Bmatrix}$$

check for optimality of \underline{x}_2 .

$$\nabla f_2 = \begin{Bmatrix} 1 + 4(-1) + 2(1) \\ -1 + 2(-1) + 2(1) \end{Bmatrix} = \begin{Bmatrix} -1 \\ -1 \end{Bmatrix} \neq \begin{Bmatrix} 0 \\ 0 \end{Bmatrix}$$

$\therefore \underline{x}_2$ is not optimum.

$$\underline{s}_2 = -\nabla f_2 = \begin{Bmatrix} 1 \\ 1 \end{Bmatrix}$$

$$\therefore \underline{x}_3 = \underline{x}_2 + \lambda_2^* \underline{s}_2$$

$$f(\underline{x}_2 + \lambda_2 \underline{s}_2) = f(-1 + \lambda_2, 1 + \lambda_2) \\ = 5\lambda_2^2 - 2\lambda_2 - 1$$

$$\therefore \frac{df}{d\lambda_2} = 10\lambda_2 - 2 = 0 \Rightarrow \lambda_2^* = \frac{1}{5}$$

$$\therefore \underline{x}_3 = \begin{Bmatrix} -1 \\ 1 \end{Bmatrix} + \frac{1}{5} \begin{Bmatrix} 1 \\ 1 \end{Bmatrix} = \begin{Bmatrix} -0.8 \\ 1.2 \end{Bmatrix}$$

$$\nabla f_3 = \begin{Bmatrix} 0.2 \\ -0.2 \end{Bmatrix} \neq \underline{0} \therefore \underline{x}_3 \text{ is not optimum.}$$

iteration 3

$$\underline{s}_3 = -\nabla f_3 = \begin{Bmatrix} -0.2 \\ 0.2 \end{Bmatrix}$$

$$f(\underline{x}_3 + \lambda_3 \underline{s}_3) = f(-0.8 - 0.2\lambda_3, 1.2 + 0.2\lambda_3)$$

$$\frac{df}{d\lambda_3} = 0 \Rightarrow \lambda_3^* = 1$$

(106)

$$\underline{x}_4 = \underline{x}_3 + \lambda_3^* \underline{s}_3$$

$$= \begin{pmatrix} -0.8 \\ 1.2 \end{pmatrix} + 1 \begin{pmatrix} -0.2 \\ 0.2 \end{pmatrix} = \begin{pmatrix} -1 \\ 1.4 \end{pmatrix} \checkmark$$

$$\nabla f_4 = \begin{pmatrix} -0.2 \\ -0.2 \end{pmatrix} \neq 0$$

$$\underline{x}^* = \begin{pmatrix} -1 \\ 1.5 \end{pmatrix}$$

c-s4

$$s_{4,2} = \begin{pmatrix} 0.2 \\ 0.2 \end{pmatrix} -$$

$$\underline{x}_5 = \underline{x}_4 + \lambda_4 \underline{s}_4$$

$$\underline{x}_5 = \begin{pmatrix} -1 \\ 1.4 \end{pmatrix} + \lambda_4 \begin{pmatrix} 0.2 \\ 0.2 \end{pmatrix}$$

$$f(-1 + 0.2\lambda_4, 1.4 + 0.2\lambda_4)$$

$$\frac{df}{d\lambda_4} = 0 ? \quad \Rightarrow \quad \lambda_4^* = \underline{0.375}$$

$$\underline{x}_5 = \begin{pmatrix} -0.2 \\ 2.15 \end{pmatrix} \checkmark \checkmark$$