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**Question:** Let  $f(x) = 10(x_2 - x_1^2)^2 + (1 - x_1)^2$ . At  $x = (0, -1)$  draw the contour lines of the quadratic model Equation 1 assuming that  $B$  is the Hessian of  $f$ . Draw the family of solutions of Equation 2 as the trust region radius varies from  $\Delta = 0$  to  $\Delta = 2$ . Repeat this at  $x = (0, 0.5)$ .

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**Quadratic Model:** Taylor-series expansion of  $f$  around  $x_k$  is,

$$f(x_k + p) = f_k + g_k^T p + \frac{1}{2} p^T \nabla^2 f(x_k + tp) p \quad (1)$$

where  $f_k = f(x_k)$  and  $g_k = \nabla f(x_k)$ , and  $t$  is some scalar in the interval  $(0, 1)$ .

By using an approximation  $B_k$  to the Hessian in the second-order term,  $m_k$  is defined as follows:

$$m_k(p) = f_k + g_k^T p + \frac{1}{2} p^T B_k p$$

where  $B_k$  is some symmetric matrix. The difference between  $m_k(p)$  and  $f(x_k + p)$  is  $\mathcal{O}(\|p\|^2)$ , which is small when  $p$  is small.

To obtain each step, we seek a solution of the subproblem,

$$\min_{p \in \mathbb{R}^n} m_k(p) = f_k + g_k^T p + \frac{1}{2} p^T B_k p \quad \text{such that } \|p\| \leq \Delta_k \quad (2)$$

where,  $\Delta_k > 0$  is the trust-region radius.

**Theorem 1:** The vector  $p^*$  is a global solution of the trust-region problem,

$$\min_{p \in \mathbb{R}^n} m(p) = f + g^T p + \frac{1}{2} p^T B p \quad \text{such that } \|p\| \leq \Delta_k$$

if and only if  $p^*$  is feasible and there is a scalar  $\lambda \geq 0$  such that the following conditions are satisfied:

$$(B + \lambda I)p^* = -g \quad (\text{condition 1})$$

$$\lambda(\Delta - \|p^*\|) = 0 \quad (\text{condition 2})$$

$$(B + \lambda I) \text{ is positive semidefinite} \quad (\text{condition 3})$$

Now, we have,

$$\begin{aligned} f(x) &= 10(x_2 - x_1^2)^2 + (1 - x_1)^2 \\ \Rightarrow \nabla f &= \begin{bmatrix} -40x_1(x_2 - x_1^2) - 2(1 - x_1) \\ 20(x_2 - x_1^2) \end{bmatrix} \\ \Rightarrow \nabla^2 f &= \begin{bmatrix} -40x_2 + 120x_1^2 + 2 & -40x_1 \\ -40x_1 & 20 \end{bmatrix} \end{aligned}$$

Now, by Theorem 1  $p^*$  is a global solution of the trust-region for Equation 2, i.e.

$$p^* = \arg \left( \min_{p \in \mathbb{R}^n} m_k(p) = f_k + g_k^T p + \frac{1}{2} p^T B_k p \right)$$

if and only if  $p^*$  is feasible and  $\exists \lambda \geq 0$  such that,

$$(B + \lambda I)p^* = -\nabla f \quad (\text{condition 1})$$

$$\lambda(\Delta - \|p^*\|) = 0 \quad (\text{condition 2})$$

$$(B + \lambda I) \geq 0 \quad (\text{condition 3})$$

## Part I: $x = (0, -1)$

At  $x = (0, -1)$ , we have the following,

$$\begin{aligned} f_k &= 10(-1 - 0^2)^2 + (1 - 0)^2 = 11 \\ g_k &= \nabla f_k = \begin{bmatrix} -40 \times 0(-1 - 0^2) - 2(1 - 0) \\ 20(-1 - 0^2) \end{bmatrix} = \begin{bmatrix} -2 \\ -20 \end{bmatrix} \\ B_k &= \nabla^2 f_k = \begin{bmatrix} -40(-1) + 120(0)^2 + 2 & -40(0) \\ -40(0) & 20 \end{bmatrix} = \begin{bmatrix} 42 & 0 \\ 0 & 20 \end{bmatrix} \end{aligned}$$

**Contour lines of the quadratic model Eq. 1:** From equation 1, we have,

$$\begin{aligned} m_k(p) &= f_k + g_k^T p + \frac{1}{2} p^T B_k p \\ &= 11 + \begin{bmatrix} -2 \\ -20 \end{bmatrix}^T \begin{bmatrix} p_1 \\ p_2 \end{bmatrix} + \frac{1}{2} \begin{bmatrix} p_1 \\ p_2 \end{bmatrix}^T \begin{bmatrix} 42 & 0 \\ 0 & 20 \end{bmatrix} \begin{bmatrix} p_1 \\ p_2 \end{bmatrix} \\ &= 11 - (2p_1 + 20p_2) + \frac{1}{2}(42p_1^2 + 20p_2^2) \\ &= 11 - 2p_1 - 20p_2 + 21p_1^2 + 10p_2^2 \end{aligned}$$

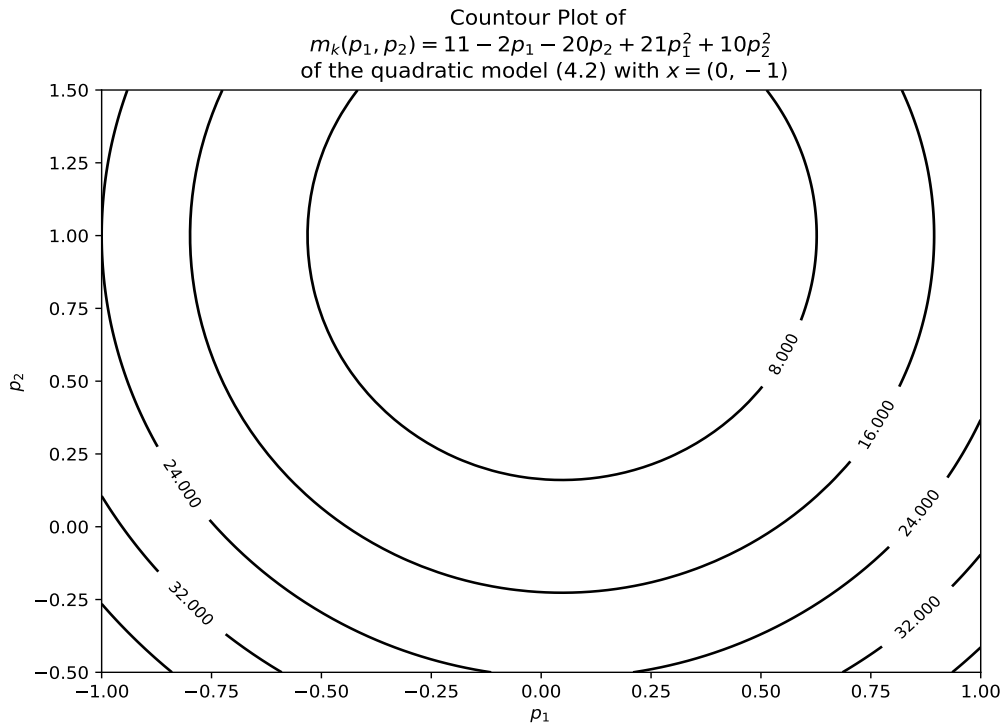


Figure 1: Contour Plot of  $m_k(p_1, p_2)$  of the quadratic model Eq. 1 with  $x = (0, -1)$

Python Code 1: Contour Plot of  $m_k(p_1, p_2)$  - the quadratic model Eq. 1 with  $x = (0, -1)$

```
1 import matplotlib
2 import numpy as np
```

```

3 import matplotlib.pyplot as plt
4
5 #Initialization
6 xmin = -1
7 xmax = 1      # x interval [xmin, xmax]
8 ymin = -0.5
9 ymax = 1.5    # y interval [ymin, ymax]
10 nx = 100     # number of points in [xmin, xmax]
11 ny = 100     # number of points in [ymin, ymax]
12 #Create x, y axis
13 x = np.linspace(xmin, xmax, nx)
14 y = np.linspace(ymin, ymax, ny)
15 #Create mesh
16 X, Y = np.meshgrid(x, y)
17 #Define fuction
18 def f(x, y):
19     return 11-2*x-20*y+21*x*x+10*y*y
20 #Evaluate functional values
21 Z = f(X, Y)
22 # Plot Contour
23 matplotlib.rcParams['contour.negative_linestyle'] = 'solid'
24 CS = plt.contour(X, Y, Z, 6, colors='k',)
25 plt.xlabel(CS, fontsize=9, inline=1)
26 plt.title("Countour Plot of \n"
27           "r\"$m_k(p_1, p_2)=11-2p_1-20p_2+21p_1^2+10p_2^2$\"
28           "\n of the quadratic model "
29           "r\"$ (4.2) $\" with " r"$x=(0,-1)$")
30 plt.xlabel(r"$p_1$")
31 plt.ylabel(r"$p_2$")
32 plt.show()

```

**The family of solutions of Eq. 2:** Now, we have to draw the family of solutions of Eq. 2 as the trust region radius varies from  $\Delta = 0$  to  $\Delta = 2$ . Let us recall, Equation 2 is,

$$\min_{p \in \mathbb{R}^n} m_k(p) = f_k + g_k^T p + \frac{1}{2} p^T B_k p \quad \text{such that } \|p\| \leq \Delta_k$$

Now, using condition 1 we have,

$$\begin{aligned}
 (B_k + \lambda I)p^* &= -\nabla f_k \\
 \Rightarrow \begin{bmatrix} 42 + \lambda & 0 \\ 0 & 20 + \lambda \end{bmatrix} p^* &= \begin{bmatrix} 2 \\ 20 \end{bmatrix} \\
 \Rightarrow p^* &= \begin{bmatrix} 42 + \lambda & 0 \\ 0 & 20 + \lambda \end{bmatrix}^{-1} \begin{bmatrix} 2 \\ 20 \end{bmatrix} \\
 \Rightarrow p^* &= \begin{bmatrix} \frac{2}{42 + \lambda} \\ \frac{20}{20 + \lambda} \end{bmatrix} \\
 \Rightarrow \|p^*\| &= \sqrt{\left(\frac{2}{42 + \lambda}\right)^2 + \left(\frac{20}{20 + \lambda}\right)^2}
 \end{aligned}$$

We seek for the solution  $p^*$  such that  $\|p^*\| \leq \Delta_k$ . Clearly,  $\arg(\max_{\lambda \geq 0} \|p^*\|) = 0$  and

$$\max_{\lambda \geq 0} \|p^*\| = \sqrt{\left(\frac{2}{42}\right)^2 + \left(\frac{20}{20}\right)^2} = \frac{\sqrt{442}}{21}$$

Hence,

$$\|p^*\| = \begin{cases} \frac{\sqrt{442}}{21} & \text{if } \lambda = 0 \\ \sqrt{\left(\frac{2}{42+\lambda}\right)^2 + \left(\frac{20}{20+\lambda}\right)^2} < \frac{\sqrt{442}}{21} & \text{if } \lambda > 0 \end{cases}$$

Now, using condition 2 we have,

$$\lambda(\Delta_k - \|p^*\|) = 0$$

Which implies from the condition  $\|p^*\| \leq \Delta_k$ ,

$$\Delta_k \in \begin{cases} \left[ \frac{\sqrt{442}}{21}, \infty \right) & \text{if } \lambda = 0 \\ \left( 0, \sqrt{\left(\frac{2}{42+\lambda}\right)^2 + \left(\frac{20}{20+\lambda}\right)^2} \right) \subseteq \left( 0, \frac{\sqrt{442}}{21} \right) & \text{if } \lambda > 0 \end{cases}$$

Thus, finally we get the solution  $p^*$  as,

$$p^* = \begin{cases} \begin{bmatrix} \frac{1}{21} \\ 1 \end{bmatrix} & \text{if } \Delta_k \in \left[ \frac{\sqrt{442}}{21}, \infty \right) \\ \begin{bmatrix} \frac{2}{42+\lambda} \\ \frac{20}{20+\lambda} \end{bmatrix} & \text{if } \Delta_k \in \left( 0, \sqrt{\left(\frac{2}{42+\lambda}\right)^2 + \left(\frac{20}{20+\lambda}\right)^2} \right) \subseteq \left( 0, \frac{\sqrt{442}}{21} \right) \end{cases}$$

Now, as the trust region radius varies from  $\Delta = 0$  to  $\Delta = 2$ , we have,

$$p^* = \begin{cases} \begin{bmatrix} \frac{1}{21} \\ 1 \end{bmatrix} & \text{if } \Delta_k \in \left[ \frac{\sqrt{442}}{21}, 2 \right) \\ \begin{bmatrix} \frac{2}{42+\lambda} \\ \frac{20}{20+\lambda} \end{bmatrix} & \text{if } \Delta_k \in \left( 0, \frac{\sqrt{442}}{21} \right) \end{cases}$$

Using Python, the trust region method has been implemented where the subproblem was handled by Newton's method.

Python Code 2: Trust region method - trust radius varies from  $\Delta = 0$  to  $\Delta = 2$  for  $x = (0, 0.5)$

```

1 import matplotlib
2 import numpy as np
3 import matplotlib.pyplot as plt
4 import matplotlib.lines as mlines
5
6 ##### Initialization #####
7 # This is the code for Part I: x = (0, -1),
8 # i.e. x1 = 0, x2 = -1 Which is the starting point
9 x0 = 0
10 y0 = -1
11 gs = 3 # Grid Size
12 ng = 500 # Grid steps
13 Dmax = 2 # Maximum TR radius
14 nD = 200 # Number of steps for Trust radius
15 nth = 200 # Angle steps

```

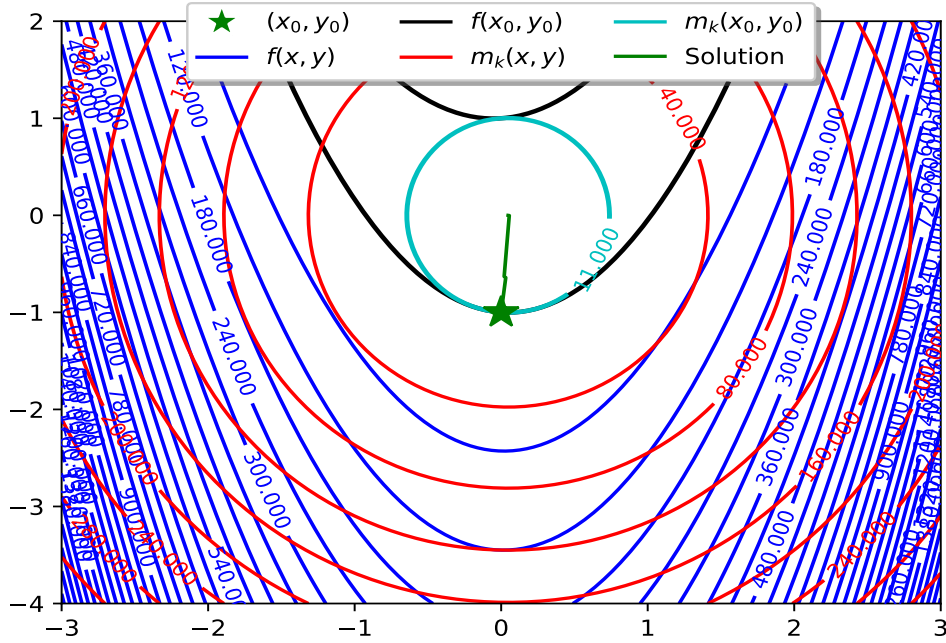


Figure 2: The family of solutions of Eq. 2 as the trust region radius varies from  $\Delta = 0$  to  $\Delta = 2$  for  $x = (0, -1)$

```

16 # Plot the initial point
17
18 #Create x, y axis
19 xmin = x0-gs
20 xmax = x0+gs
21 ymin = y0-gs
22 ymax = y0+gs
23 x = np.linspace(xmin, xmax, ng)
24 y = np.linspace(ymin, ymax, ng)
25 #Create mesh
26 X, Y = np.meshgrid(x, y)
27 #Define fuction
28 def f(x, y):
29     return 10*np.multiply(((y-np.multiply(x,x))),((y-np.multiply(x,x)))) +
30         np.multiply(1-x,1-x)
31 #Evaluate functional values
32 Z = f(X, Y)
33 f0 = 10*(y0-x0**2)**2 + (1-x0)**2; # initial function values
34 g0 = np.matrix([[ -40*x0*(y0-x0**2)-2*(1-x0) ], [ 20*(y0-x0**2) ]])
35 B0 = np.matrix([[ 120*x0**2-40*y0+2, -40*x0 ], [ -40*x0, 20 ]])
36 M = f0 + g0.item(0)*(X-x0)+g0.item(1)*(Y-y0) + 0.5*B0.item((0,0))*np.
37     multiply((X-x0),(X-x0)) + B0.item((0,1))*np.multiply((X-x0),(Y-y0)) +
38     0.5*B0.item((1,1))*np.multiply((Y-y0),(Y-y0))
39 # Plot Contour
40 plt.plot([x0], [y0], 'g*', markersize=15)
41 x0y0_legend = mlines.Line2D([], [], color='w', marker='*', markerfacecolor=
42     'g',
43     markersize=15, label='$ (x_0, y_0) $')

```

```

40
41 matplotlib.rcParams[ 'contour.negative.linestyle' ] = 'solid'
42 CS = plt.contour(X, Y, Z, 30, colors='b', )
43 plt.xlabel(CS, fontsize=9, inline=1)
44 f_legend = mlines.Line2D([], [], color='b', label='$f(x,y)$')
45
46 CS = plt.contour(X, Y, Z, levels = [f0],
47                  colors=('k',), linestyle=('--',), linewidths=(2,))
48 plt.xlabel(CS, fontsize=9, inline=1)
49 f_legend0 = mlines.Line2D([], [], color='k', label='$f(x_0,y_0)$')
50
51 CS = plt.contour(X, Y, M, 8, colors='r',)
52 plt.xlabel(CS, fontsize=9, inline=1)
53 M_legend = mlines.Line2D([], [], color='r', label='$m_k(x,y)$')
54
55 CS = plt.contour(X, Y, M, levels = [f0],
56                  colors=('c',), linestyle=('--',), linewidths=(2,))
57 plt.xlabel(CS, fontsize=9, inline=1)
58 M_legend0 = mlines.Line2D([], [], color='c', label='$m_k(x_0,y_0)$')
59 # Solving subproblem
60 pN = -np.linalg.inv(B0)*g0 #Newton Step
61 XN = x0 + pN.item(0)
62 YN = y0 + pN.item(1)
63 MN = f0 + g0.item(0)*(XN-x0)+g0.item(1)*(YN-y0) + 0.5*B0.item((0,0))*np.
        multiply((XN-x0),(XN-x0)) + B0.item((0,1))*np.multiply((XN-x0),(YN-y0))
        + 0.5*B0.item((1,1))*np.multiply((YN-y0),(YN-y0))
64 dD = Dmax/nD
65 xtc = np.zeros(nD)
66 ytc = np.zeros(nD)
67 th = np.linspace(0,2*np.pi,nth)
68 ct = np.cos(th)
69 st = np.sin(th)
70 for k in range(1, nD+1):
71     Delta = k*dD;
72     X = x0 + Delta*ct
73     Y = y0 + Delta*st
74     M = f0 + g0.item(0)*(X-x0)+g0.item(1)*(Y-y0) + 0.5*B0.item((0,0))*np.
        multiply((X-x0),(X-x0)) + B0.item((0,1))*np.multiply((X-x0),(Y-y0)) +
        0.5*B0.item((1,1))*np.multiply((Y-y0),(Y-y0))
75     lowpt = [i for i, v in enumerate(M) if v == min(M)] # minpos = [i for i
        , v in enumerate(array name here) if v == min(array name here)]
76     lowpt = lowpt[0]
77     nP = np.linalg.norm(np.subtract([XN, YN],[x0,y0]))
78     if (nP>Delta) or (MN > M[lowpt]):
79         xtc[k-1] = X[lowpt];
80         ytc[k-1] = Y[lowpt];
81     else :
82         xtc[k-1] = XN;
83         ytc[k-1] = YN;
84 Ax = np.insert(xtc,0,x0)
85 Ay = np.insert(ytc,0,y0)
86 plt.plot(Ax, Ay, 'g')
87 sol_legend = mlines.Line2D([], [], color='g', label='Solution')
88 plt.legend(handles=[x0y0_legend, f_legend, f_legend0, M_legend, M_legend0,
        sol_legend],loc='upper center', bbox_to_anchor=(0.5, 1.05),ncol=3,
        fancybox=True, shadow=True)
89 plt.show()

```

## Part II: $x = (0, 0.5)$

Using the exact same process we have the following output.

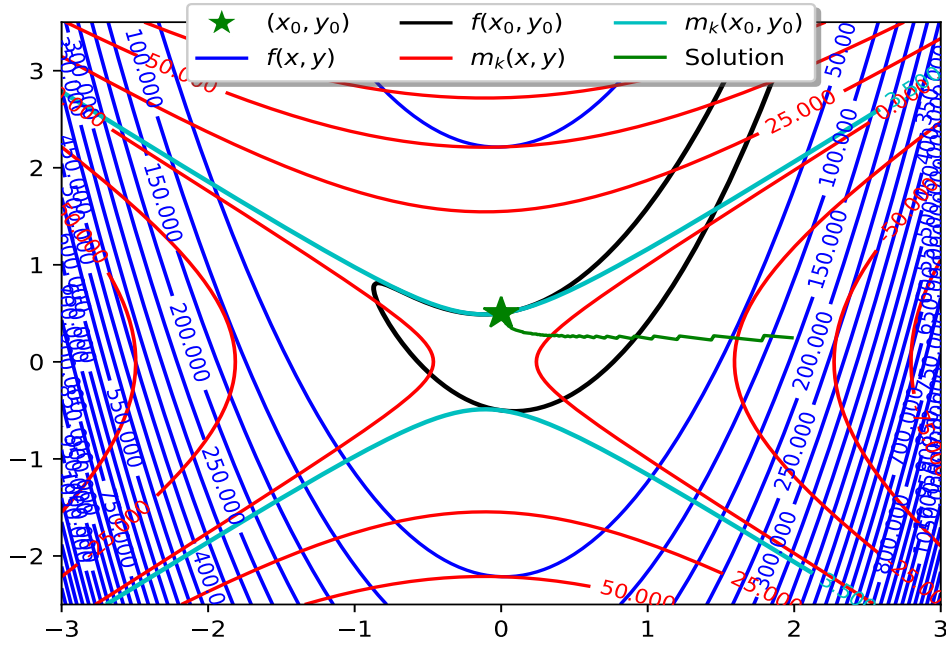


Figure 3: The family of solutions of Eq. 2 as the trust region radius varies from  $\Delta = 0$  to  $\Delta = 2$  for  $x = (0, 0.5)$  and the Countour Plot of  $m_k(p_1, p_2)$  of the quadratic model Eq. 1 with  $x = (0, 0.5)$