

Numerical Optimization HW04

December 17, 2021

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1 Multivariate Optimization

Multivariate Optimization for smooth function - The method of steepest descent - Newton's method
- Quasi-Newton's method : SR1, BFGS

In this notebook, we will optimize three functions

$$f(x, y) = (x + 2y - 6)^2 + (2x + y - 6)^2$$

$$f(x, y) = 50(y - x^2)^2 + (1 - x)^2$$

$$f(x, y) = (1.5 - x + xy)^2 + (2.25 - x + xy^2)^2 + (2.625 - x + xy^3)^2$$

1.0.1 Iteration formular

$x_{k+1} := x_k + \alpha_k p_k$ where α_k is step length and p_k is search direction

Method of Steepest Descent $p_k = -\nabla f(x_k)$

Newton's Method $p_k = -(\nabla^2 f(x_k))^{-1} \nabla f(x_k)$

Quasi Newton's Method $p_k = -\mathbf{B}_k^{-1} \nabla f(x_k)$ where $\mathbf{B}_k \approx (\nabla^2 f(x_k))$

2 Implementation

```
[1]: %matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.tri as tri
import math as m
import time as t
from tabulate import tabulate
```

2.0.1 Define Function

```
[2]: def f_1(p):
      x, y = p[0][0], p[1][0]
      return (x+2*y-6)**2+(2*x+y-6)**2
def f_2(p):
      x, y = p[0][0], p[1][0]
      return 50*(y-x**2)**2+(1-x)**2
def f_3(p):
      x, y = p[0][0], p[1][0]
      return (1.5-x+x*y)*2+(2.25-x+x*(y**2))*2+(2.625-x+x*(y**3))*2
```

2.0.2 Define Plotting Function

```
[3]: def plotContour(f, rangeX=(0, 0), rangeY=(0, 0), grid=(0, 0)):
      x = np.arange(*rangeX, 0.01)
      y = np.arange(*rangeY, 0.01)
      X, Y = np.meshgrid(x, y)
      Z = f([X], [Y])
      plt.figure(figsize=grid)
      cp = plt.contour(X, Y, Z, levels=np.linspace(
          Z.reshape(-1, 1).min(), Z.reshape(-1, 1).max(), 120), linewidths=0.1)
      ↪ # plt.colorbar(cp)

def plotLine(x1, x2, color="black"):
      plt.plot([x1[0], x2[0]], [x1[1], x2[1]], color, linewidth=.8)

def plotPoint(x, color="black"):
      plt.plot([x[0]], [x[1]], color, marker='o', markersize=4)

def plotText(x, str=None):
      plt.plot([x[0]], [x[1]], "black", marker='o', markersize=4)
      if str != None:
          plt.text(x[0]+.03, x[1]+.03, str, fontsize=20)
      else:
          plt.text(x[0]+.03, x[1]+.03, "(%.3f, %.3f)" % x, fontsize=20)

def resultsInTable(x, f):
      print("\n%s results at (%.2f, %.2f)" % (f.__name__, x.T[0][0], x.T[0][1]))
      if f == f_1:
          print("minimum value of f1 is 0.0 at (2,2)")
      elif f == f_2:
          print("minimum value of f2 is 0.0 at (1,1)")
```

```

elif f == f_3:
    print("minimum value of f3 is 6.16298e-32 at (3,0.5)")
    plotText(x, "x0")
    sd = steepestDescent(x.copy(), f, color="purple")
    ne = newton(x.copy(), f, color="green")
    sr1 = quasiNewtonSR1(x.copy(), f, color="red")
    bfgs = quasiNewtonBFGS(x.copy(), f, color="blue")
    print(tabulate(["S.D", *sd], ["Newton", *ne], ["SR1", *sr1], ["BFGS", *bfgs],
        headers=["f(x)", "x", "iter", "time"], tablefmt="github",
        floatfmt=(".5f", ".5f")))
    return
def printVal(xk, f, iter, start):
    return "%.8f" % f(xk), "(%.8f, %.8f)" % (xk.T[0][0], xk.T[0][1]), iter, "%4.2f"%((t.time()-start)*1000)

```

2.0.3 Gradient and Hessian Implementation

```

[4]: def grad(p, f):
    dx = np.array([[[-h], [0]], [[h], [0]]])
    dy = np.array([[0], [-h]], [[0], [h]]])
    g1 = (f(p+dx[1])-f(p+dx[0]))/(2*h)
    g2 = (f(p+dy[1])-f(p+dy[0]))/(2*h)
    g = np.array([g1, g2])
    return g

def hessian(p, f):
    dx = np.array([[[-h], [0]], [[h], [0]]])
    dy = np.array([[0], [-h]], [[0], [h]]])
    H11 = (f(p+2*dx[1])-2*f(p)+f(p+2*dx[0]))/(4*h**2)
    H12 = (f(p+dx[1]+dy[1])-f(p+dx[1]+dy[0]) -
        f(p+dx[0]+dy[1])+f(p+dx[0]+dy[0]))/(4*h**2)
    H21 = H12
    H22 = (f(p+2*dx[1])-2*f(p)+f(p+2*dx[0]))/(4*h**2)
    H = np.array([H11, H12], [H21, H22])
    return H

```

2.0.4 Backtracking Method for step length

```

[5]: def stepLength(x0, p, f): # Use backtrakingMethod
    a0 = 3
    r = 0.9
    c = 0.6
    a = a0
    while True:
        if f(x0+a*p) > a*c*np.dot(grad(x0, f).T, p)+f(x0):
            a *= r

```

```

    else:
        break
    return a

```

2.0.5 Method of Steepest descent

```

[6]: def steepestDescent(x0, f, color="black"):
    iter, start = 0, t.time()
    xk = x0
    while True:
        pk = -grad(xk, f)
        pk /= np.linalg.norm(pk)
        sk = stepLength(xk, pk, f)*pk
        plotLine(xk, xk+sk, color)
        plotPoint((xk.T[0][0], xk.T[0][1]), color)

        xk += sk

        iter += 1
        if np.linalg.norm(sk) <= eps:
            plt.plot(xk.T[0][0], xk.T[0][1], color, marker='o', markersize=6)
            break
    return printVal(xk, f, iter, start)

```

2.0.6 Newton's Method

```

[7]: def newton(x0, f, color="black"):
    iter, start = 0, t.time()
    xk = x0
    while True:
        dfx = grad(xk, f)
        Hk = hessian(xk, f)
        pk = -np.matmul(np.linalg.inv(Hk), dfx)
        pk /= np.linalg.norm(pk)
        sk = stepLength(xk, pk, f)*pk
        plotLine(xk, xk+sk, color)
        plotPoint((xk.T[0][0], xk.T[0][1]), color)
        xk += sk
        iter += 1

        if np.linalg.norm(sk) <= eps:
            plt.plot(xk.T[0][0], xk.T[0][1], color, marker='o', markersize=6)
            break
    return printVal(xk, f, iter, start)

```

2.0.7 Quasi-Newton's Method with rank 1 : SR1 Method

```
[8]: def quasiNewtonSR1(x0, f, color="black"):
    iter, start = 0, t.time()
    I = np.array([[1, 0], [0, 1]])
    sk, yk, Hk = np.array([[1, 0]]).T, np.array([[1, 0]]).T, I
    pk = np.array([[1, 0]]).T
    xk = x0
    while True:
        dfx = grad(xk, f)
        pk = -np.matmul(Hk, dfx)
        pk /= np.linalg.norm(pk)
        sk = stepLength(xk, pk, f)*pk
        plotLine(xk, xk+sk, color)
        plotPoint((xk.T[0][0], xk.T[0][1]), color)
        xk += sk
        yk = grad(xk, f)-dfx
        Hk = Hk+(sk-np.matmul(Hk, yk))*(sk-np.matmul(Hk, yk)).T / (np.
        ↪dot((sk-np.matmul(Hk, yk)).T, yk))
        iter += 1
        if np.linalg.norm(sk) <= eps:
            plt.plot(xk.T[0][0], xk.T[0][1], color, marker='o', markersize=6)
            break
    return printVal(xk, f, iter, start)
```

2.0.8 Quasi-Newton's Method with rank 2 : BFGS

```
[9]: def quasiNewtonBFGS(x, f, color="black"):
    iter, start = 0, t.time()
    I = np.array([[1, 0], [0, 1]])
    sk, yk, Hk = np.array([[1, 0]]).T, np.array([[1, 0]]).T, I
    pk = np.array([[1, 0]]).T
    xk = x
    while True:
        dfx = grad(xk, f)
        pk = -np.matmul(Hk, dfx)
        pk /= np.linalg.norm(pk)

        sk = stepLength(xk, pk, f)*pk
        plotLine(xk, xk+sk, color)
        plotPoint((xk.T[0][0], xk.T[0][1]), color)
        xk += sk
        yk = grad(xk, f)-dfx

        rk = 1/(np.dot(yk.T, sk))
        Hk = (I-rk*sk*yk.T)*Hk*(I-rk*yk*sk.T)+rk*sk*sk.T
```

```

    iter += 1
    if np.linalg.norm(sk) <= eps:
        plt.plot(xk.T[0][0], xk.T[0][1], color, marker='o', markersize=6)
    break
return printVal(xk, f, iter, start)

```

3 Results

3.0.1 Optimize result at point $x_0 = (1.2, 1.2)$

```

[10]: h = 1e-7
      eps = 1e-5
      x0 = np.array([[1.2, 1.2]]).T
      plotContour(f_1, rangeX=(1, 2.25), rangeY=(1, 2.25), grid=(8, 8))
      resultsInTable(x0.copy(), f_1)
      plotContour(f_2, rangeX=(0.9, 1.4), rangeY=(0.95, 1.45), grid=(7.5, 9))
      resultsInTable(x0.copy(), f_2)
      plotContour(f_3, rangeX=(-0.5, 5.0), rangeY=(-1, 1.3), grid=(16, 8))
      resultsInTable(x0.copy(), f_3)

```

f_1 results at (1.20, 1.20)

minimum value of f1 is 0.0 at (2,2)

	f(x)	x	iter	time
S.D	0.00000	(1.99999769, 1.99999769)	9	37.4
Newton	0.00000	(1.99999769, 1.99999769)	9	37.23
SR1	0.00000	(1.99999769, 1.99999769)	9	30.57
BFGS	0.72632	(1.79912352, 1.79912352)	1	1.41

f_2 results at (1.20, 1.20)

minimum value of f2 is 0.0 at (1,1)

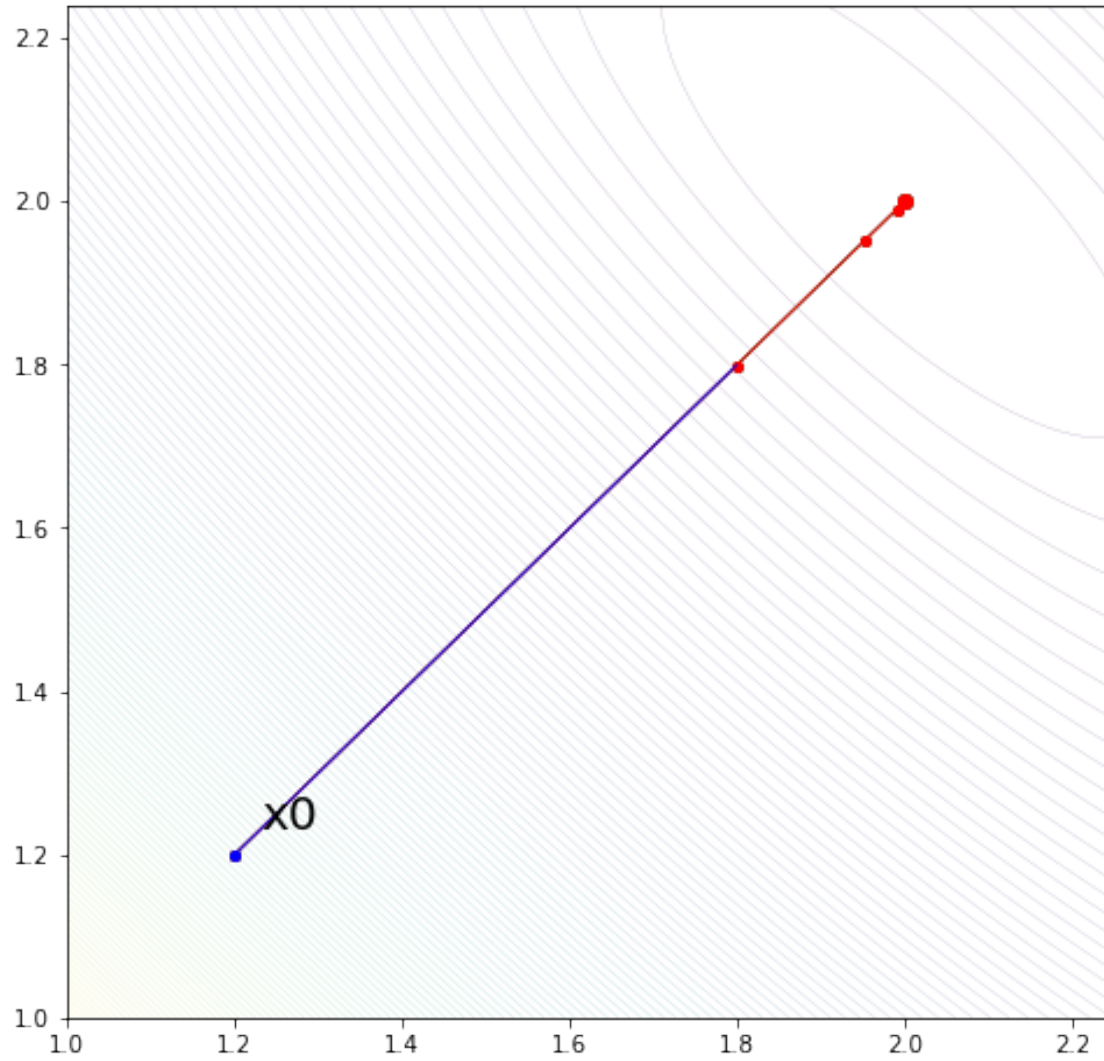
	f(x)	x	iter	time
S.D	0.00001	(1.00257874, 1.00518998)	141	752.91
Newton	0.00000	(1.00065820, 1.00132666)	83	417.3
SR1	0.00223	(1.02552932, 1.04609425)	7	35.49
BFGS	0.25134	(1.13755014, 1.22584132)	1	3.11

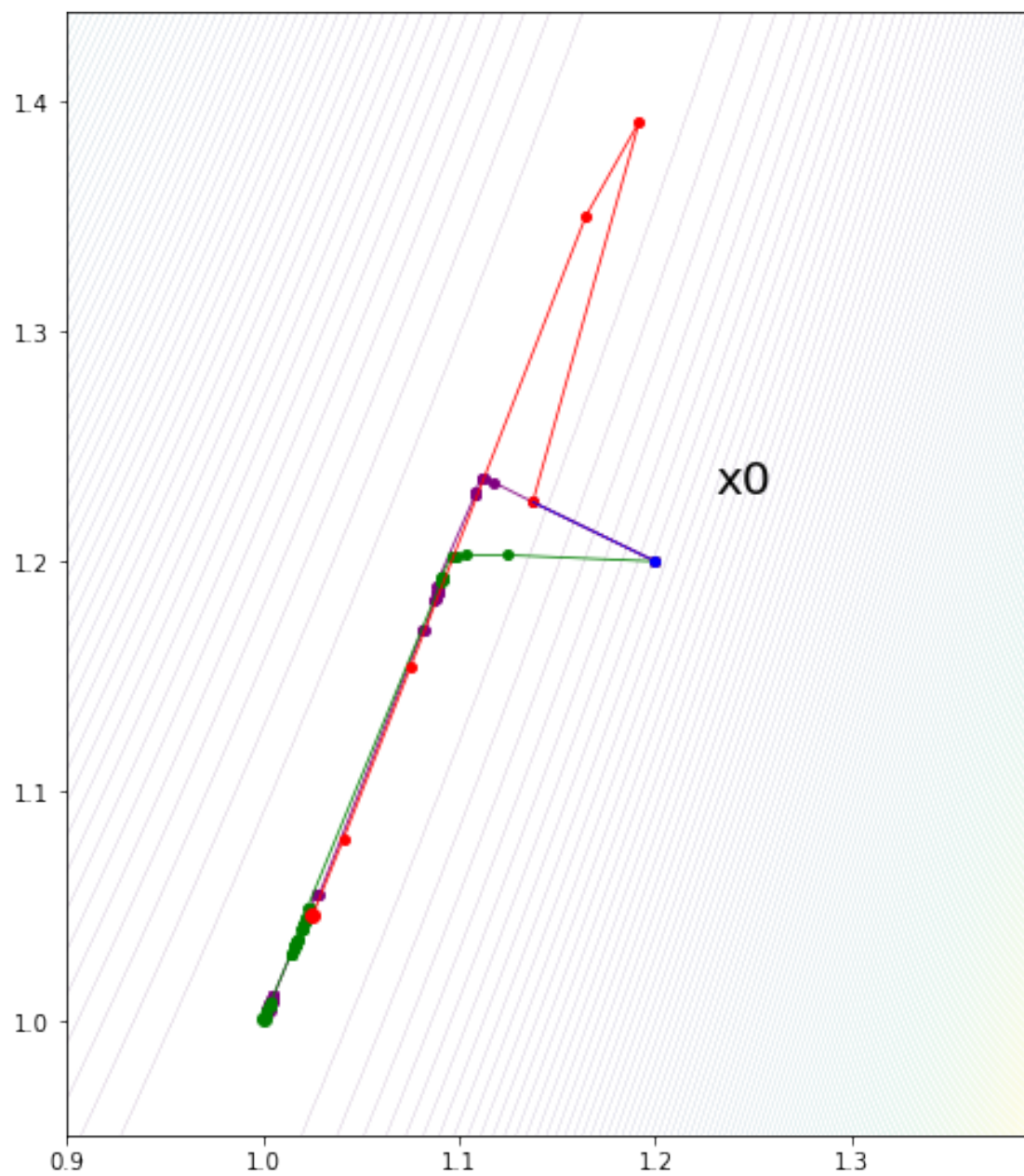
f_3 results at (1.20, 1.20)

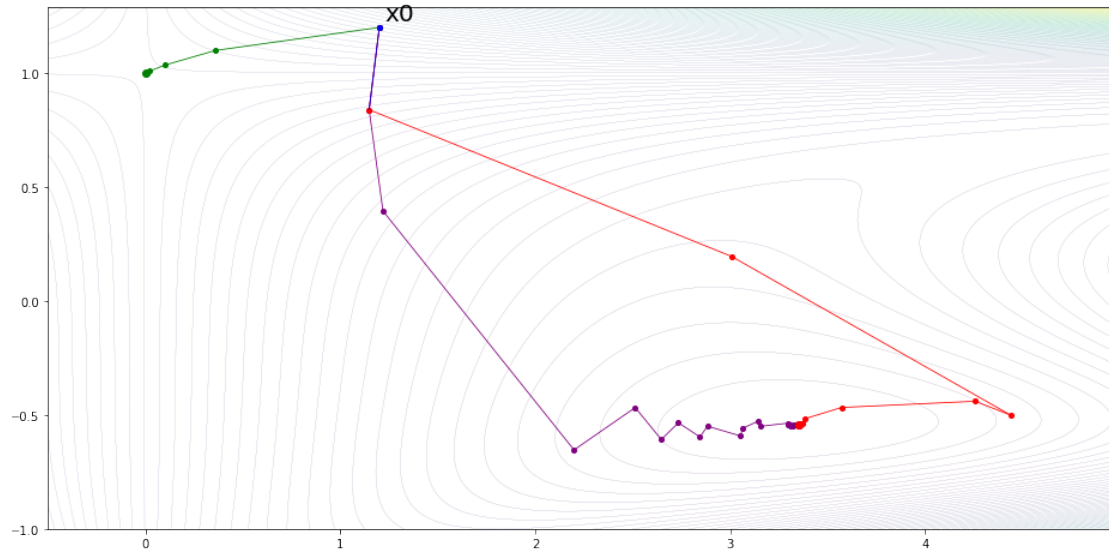
minimum value of f3 is 6.16298e-32 at (3,0.5)

	f(x)	x	iter	time
S.D	-5.73452	(3.34993582, -0.54359493)	52	274.54
Newton	14.95312	(0.00000068, 1.00000028)	10	44.74
SR1	-5.73452	(3.35002111, -0.54359041)	14	51.86

| BFGS | 10.92526 | (1.14759193, 0.83905493) | 1 | 2.07 |







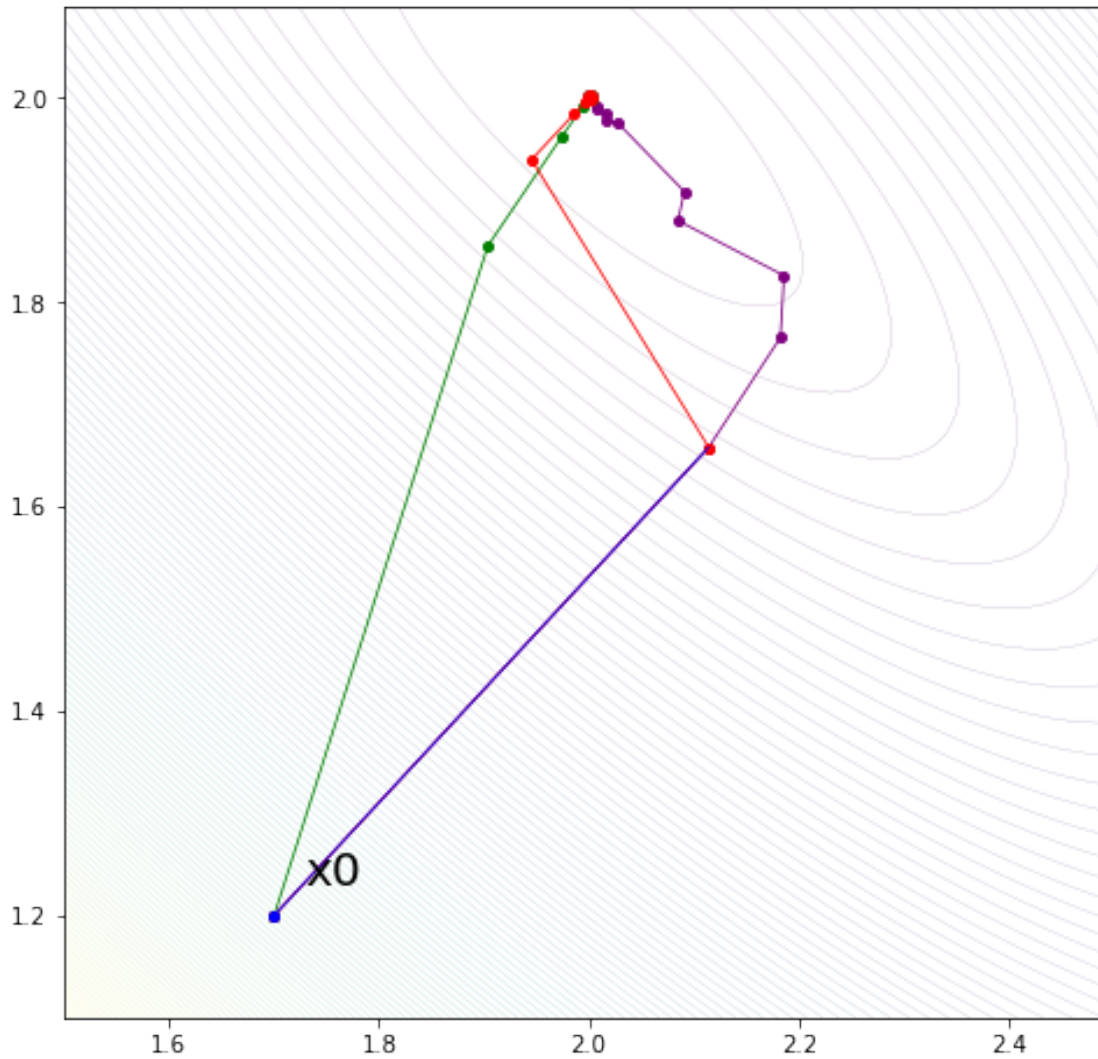
3.0.2 $f(x, y) = (x + 2y - 6)^2 + (2x + y - 6)^2$
with initial point $x_0 = (1.7, 1.2)$

```
[11]: x0 = np.array([[1.7, 1.2]]).T
      plotContour(f_1, rangeX=(1.5, 2.5), rangeY=(1.1, 2.1), grid=(8, 8))
      resultsInTable(x0.copy(), f_1)
```

f_1 results at (1.70, 1.20)

minimum value of f1 is 0.0 at (2,2)

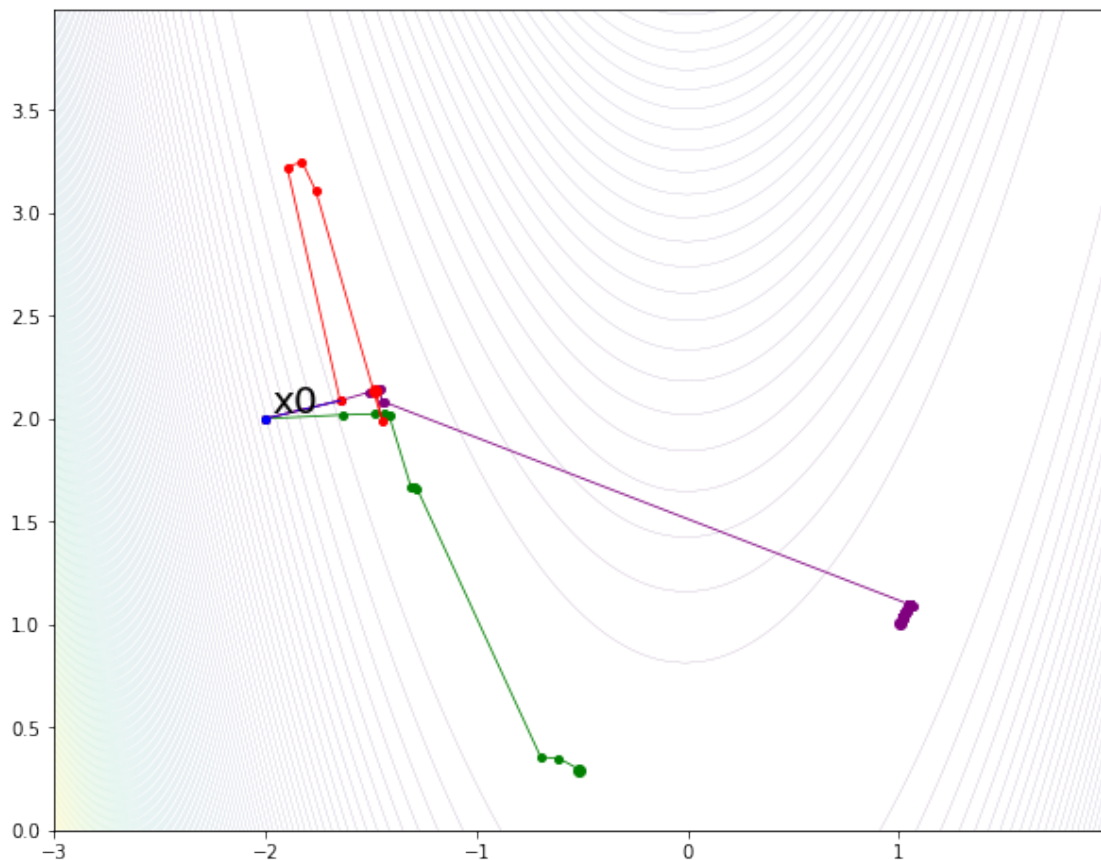
	f(x)	x	iter	time
-----	-----	-----	-----	-----
S.D	0.00000	(2.00002634, 1.99997339)	23	86.45
Newton	0.00000	(1.99999892, 1.99999842)	9	30.16
SR1	0.00000	(1.99999762, 1.99999738)	9	30.12
BFGS	0.33703	(2.11417451, 1.65823563)	1	1.47



```
[12]: x0 = np.array([[-2.0, 2.0]]).T
      plotContour(f_2, rangeX=(-3, 2), rangeY=(0, 4), grid=(10, 8))
      resultsInTable(x0.copy(), f_2)
```

f_2 results at (-2.00, 2.00)
minimum value of f2 is 0.0 at (1,1)

	f(x)	x	iter	time
-----	-----	-----	-----	-----
S.D	0.00001	(1.00263885, 1.00531048)	175	785.67
Newton	2.33778	(-0.51228736, 0.29430263)	12	181.97
SR1	6.23975	(-1.47807752, 2.14024307)	7	28.5
BFGS	26.31410	(-1.64600549, 2.08783983)	1	2

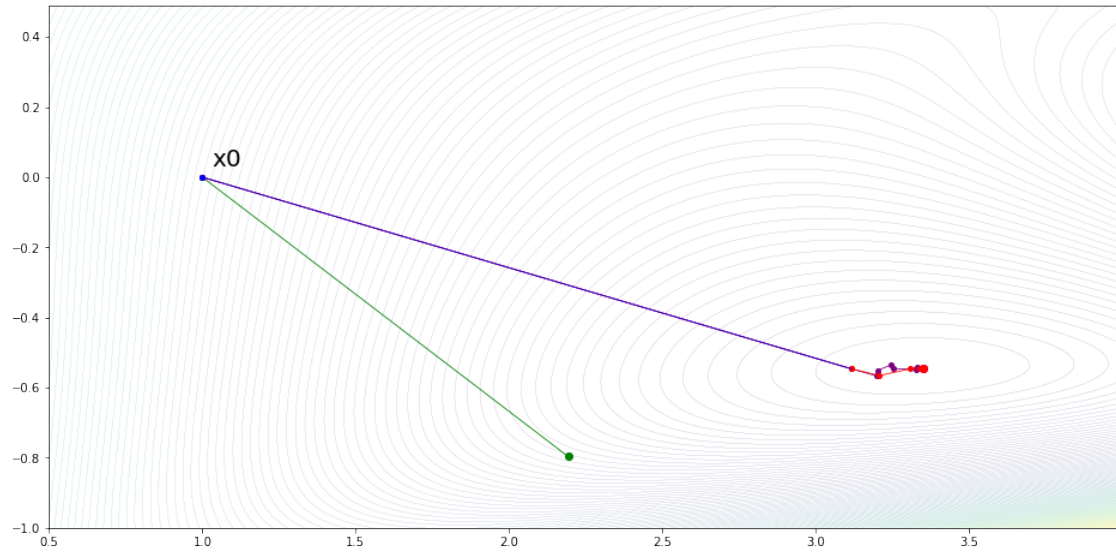


```
[13]: x0 = np.array([[1.0, 0.0]]).T
      plotContour(f_3, rangeX=(0.5, 4), rangeY=(-1, 0.5), grid=(16, 8))
      resultsInTable(x0.copy(), f_3)
```

f_3 results at (1.00, 0.00)

minimum value of f3 is 6.16298e-32 at (3,0.5)

	f(x)	x	iter	time
-----	-----	-----	-----	-----
S.D	-5.73452	(3.35000389, -0.54358946)	25	98.77
Newton	-2.32565	(2.19349702, -0.79654014)	2	16.6
SR1	-5.73452	(3.35001809, -0.54359066)	10	34.8
BFGS	-5.63581	(3.11762251, -0.54648323)	1	1.05



[]: