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CMPS 351

Assignment 2

```
In [1]: 1 import numpy as np
        2 from numpy import linalg as la
        3 import matplotlib.pyplot as plt
```

Rosenbrock

```
In [2]: 1 def rosenbrock(x):
        2     f = 10 * (x[1] - x[0]**2)**2 + (1 - x[0])**2
        3     return f
```

Rosenbrock Gradient

```
In [3]: 1 def rosenbrock_gradient(x):
        2     g = np.zeros(2)
        3     g[0] = -40*x[0]*(x[1] - x[0]**2) + 2*x[0] - 2
        4     g[1] = 20*x[1] - 20*x[0]**2
        5     return g
```

Rosenbrock Hessian

```
In [4]: 1 def rosenbrock_hessian(x):
        2     h = np.array([np.zeros(2), np.zeros(2)])
        3     h[0, 0] = 120*x[0]**2 - 40*x[1] + 2
        4     h[0, 1] = -40*x[0]
        5     h[1, 0] = -40*x[0]
        6     h[1, 1] = 20
        7     return h
```

Backtrack Line Search

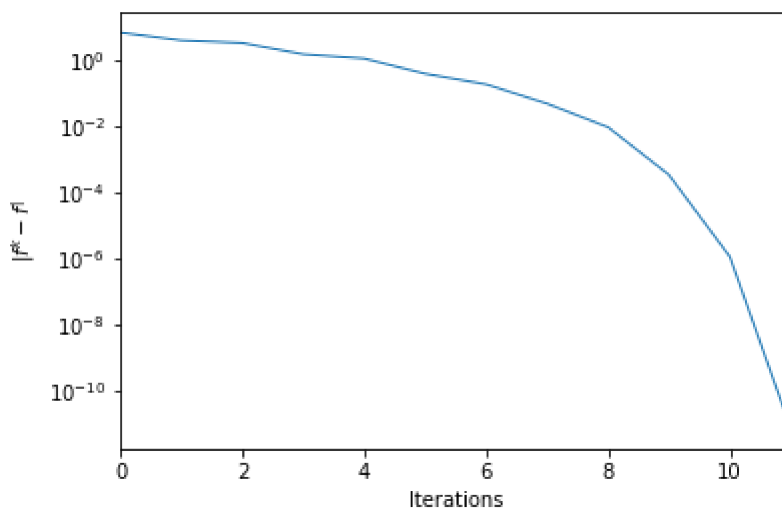
```
In [5]: 1 def backtrack_linesearch(f, gk, pk, xk, alpha = 0.01, beta = 0.6):
        2     t = 1
        3     while ( f(xk + t*pk) > f(xk) + alpha*t*gk@pk):
        4         t *= beta
        5     return t
```

Newton Backtrack Line Search

```
In [6]: 1 def newton_backtrack(f, grad, hess, x0, tol = 1e-5):
2         x = x0
3         history = np.array([x0])
4         while (la.norm(grad(x)) > tol):
5             p = la.solve(hess(x), -grad(x))
6             t = backtrack_linesearch(f, grad(x), p, x)
7             x += t * p
8             history = np.vstack((history, x))
9         return x, history
```

Plotting the performance

```
In [7]: 1 x0 = np.array([-1.2, 1.0])
2 xstar, history = newton_backtrack(rosenbrock, rosenbrock_gradient, rosenbrock_hessian, x0)
3
4 nsteps = history.shape[0]
5 fhist = np.zeros(nsteps)
6
7 for i in range(nsteps):
8     fhist[i] = rosenbrock(history[i,:])
9
10 plt.figure()
11 plt.autoscale(enable=True, axis='x', tight=True)
12 plt.semilogy(np.arange(0, nsteps), fhist, linewidth=1)
13 plt.xlabel('Iterations')
14 plt.ylabel(r'$|f^k - f^*|$')
15 plt.show()
```



Near the minimum, the algorithm converges quadratically

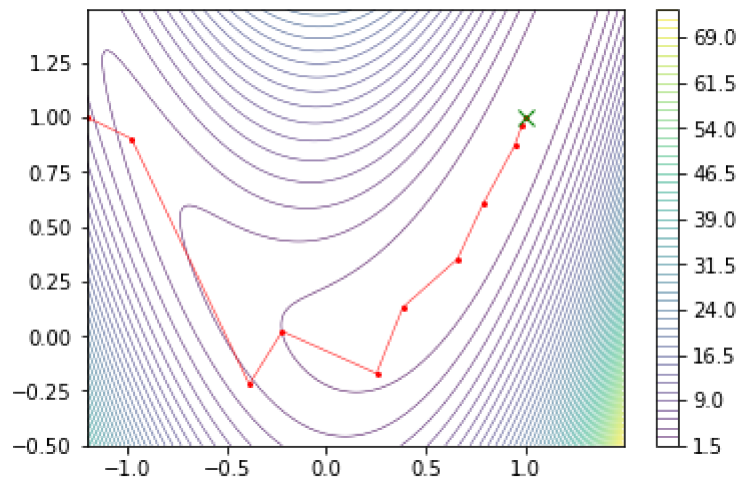
$$|f^{k+1} - f^*| < C|f^k - f^*|^2$$

Steepest descent converged linearly on the plot, and took over 1000 iterations to reach the local minimum. Newton's method converged in 11 iterations and made more progress the closer it got to the minimum

Plotting the contours

```
In [8]: 1 x0 = np.arange(-1.2, 1.5, 0.01)
2 x1 = np.arange(-0.5, 1.5, 0.01)
3
4 F = np.zeros((x1.shape[0], x0.shape[0]))
5
6 for i in range(F.shape[0]):
7     for j in range(F.shape[1]):
8         x = [x0[j], x1[i]]
9         F[i, j] = rosenbrock(x)
10
11 plt.figure('Contours')
12 plt.plot(history[:,0], history[:,1], linewidth=0.5, color='red', marker='o',
13 plt.plot([1],[1], color='green', marker='x', markersize=8)
14 plt.contour(x0, x1, F, 50, linewidths=0.5)
15 #plt.axis('equal')
16 plt.colorbar()
```

Out[8]: <matplotlib.colorbar.Colorbar at 0x2372a7f4fd0>



Function in R^{100}

$$f(x) = - \sum_{i=1}^{500} \log(1 - a_i^t x) - \sum_{i=1}^{100} \log(1 - x_i^2)$$

```
In [9]: 1 def f(a, x):
2     try:
3         f1 = 0
4         for at in a:
5             f1 += np.log10(1 - at*x)
6         f2 = np.sum(np.log10(1 - x**2))
7         return - f1 - f2
8     except:
9         return np.nan
```

R^{100} Gradient

$$f(x) \frac{\partial}{\partial x_j} = \sum_{i=1}^{500} \frac{a_{ij}}{\ln(10)(1 - a_i^t x)} + \frac{2x_j}{\ln(10)(1 - x_j^2)}$$

```
In [10]: 1 def f_gradient(a, x):
2         g = np.zeros(100)
3         for j in range(100):
4             term1 = 0
5             for i in range(500):
6                 term1 += a[i, j]/(np.log(10)*(1 - a[i]*x))
7             g[j] = term1 + 2*x[j]/(np.log(10)*(1 - x[j]**2))
8         return g
```

R¹⁰⁰ Hessian

$$f(x) \frac{\partial^2}{\partial x_j \partial x_k} = \begin{cases} \sum_{i=1}^{500} \frac{a_{ij}a_{ik}}{\ln(10)(1 - a_i^t x)^2} & \text{where } k \neq j \\ \sum_{i=1}^{500} \frac{a_{ij}^2}{\ln(10)(1 - a_i^t x)^2} + \frac{2 + 2x_j^2}{\ln(10)(1 - x_j^2)^2} & \text{where } k = j \end{cases}$$

```
In [11]: 1 def f_hessian(a, x):
2         h = np.zeros([100,100])
3         for k in range(100):
4             for j in range(100):
5                 term1 = 0
6                 for i in range(500):
7                     term1 += a[i, j]*a[i, k]/(np.log(10)*(1 - a[i]*x)**2)
8                 if k == j:
9                     h[k, j] = term1
10                else:
11                    h[k, j] = term1 + (2 + 2*x[j]**2)/(np.log(10)*(1 - x[j]**2)**2)
12            return h
```

The system of equations needed to be solved at every iteration can be written as

$$\nabla^2 f(x) \cdot x = -\nabla f(x)$$

Modified Backtrack Line Search

```
In [12]: 1 def backtrack_linesearch_mod(f, gk, pk, xk, a, alpha = 0.01, beta = 0.6):
2         t = 1
3         while (np.isnan(f(a, xk + t*pk)) or f(a, xk + t*pk) > f(a, xk) + alpha*t*
4             t *= beta
5         return t
```

Modified Newton Backtrack

```
In [13]: 1 def newton_backtrack_mod(f, grad, hess, x0, a, tol = 1e-5):
2         x = x0
3         history = np.array([x0])
4         while (la.norm(grad(a, x)) > tol):
5             p = la.solve(hess(a, x), -grad(a, x))
6             t = backtrack_linesearch_mod(f, grad(a, x), p, x, a)
7             x += t * p
8             #print(la.norm(grad(a, x)))
9             history = np.vstack((history, x))
10        return x, history
```

Plotting Performance in R^{100}

```
In [14]: 1 x0 = np.array(np.zeros(100))
2         a = np.random.randn(500, 100)
3         xstar, history = newton_backtrack_mod(f, f_gradient, f_hessian, x0, a)
```

C:\Users\Danny\Anaconda3\lib\site-packages\ipykernel_launcher.py:5: RuntimeWarning: invalid value encountered in log10
 """

```
In [15]: 1 nsteps = history.shape[0]
2         fhist = np.zeros(nsteps)
3         fstar = f(a, xstar)
4
5         for i in range(nsteps):
6             fhist[i] = f(a, history[i,:])
7             #print(fhist[i])
8
9         plt.figure()
10        plt.autoscale(enable=True, axis='x', tight=True)
11        plt.semilogy(np.arange(0, nsteps), abs(fhist - fstar), linewidth=1)
12        plt.xlabel('Iterations')
13        plt.ylabel(r'$|f^k - f^*|$')
14        plt.show()
```

