3rd Assignment

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1 Group Members

Pierre Mercatoris – Pablo Bordons Estrada - Sergio Gámez Ruiz de Olano – Mohammadmehdi Fayazbakhsh

```
In [72]: %matplotlib notebook
         from __future__ import division
         import numpy as np
         import time
         nsample = 1000
         nvariables = 100
         X0=np.ones([nsample, 1])
         X1=np.random.uniform(0, 10, ([nsample, nvariables]))
         X=np.concatenate([X0, X1], axis=1)
         error=np.random.normal(0, 1, (nsample,1)) # Normal random error
         beta=np.random.uniform(-5, 5, size=([nvariables+1, 1]))
         Y=np.dot(X, beta)+error
         print (beta)
[[ 1.28069035]
 [ 2.12055007]
 [-3.35364129]
 [ 2.49180722]
 [-2.8342821]
 [ 2.01194948]
 [-2.85385757]
 [ 0.3348794 ]
 [ 1.54505771]
 [ 3.76039123]
 [-3.08866171]
 [-0.51838654]
 [ 4.079594 ]
 [ 3.20824974]
 [ 4.02375764]
 [ 1.82350012]
 [ 2.73740613]
```

- [4.83990623]
- [4.78336779]
- [-2.28676607]
- [-2.59697585]
- [-4.13702962]
- [-2.42724456]
- [4.51397344]
- [-4.76847074]
- [4.55519664]
- [4.76617981]
- [-0.63032856]
- [-4.11676195]
- [1.24741552]
- [-3.9683488]
- [-1.08071633]
- [-0.25369959]
- [-2.47735284]
- [2.05335703]
- [4.89243931]
- [2.84978551]
- [0.31243966]
- [4.83657486]
- [0.43747194]
- [-0.77572563]
- [3.27644737]
- [-1.55841983]
- [0.09359911]
- [2.1735441]
- [1.83173806]
- [4.21374777]
- [2.44924523]
- [-0.69330504]
- [-1.93368367]
- [4.97225515] [2.40465098]
- [-2.23907213]
- [4.66306122]
- [-2.9983419]
- [-2.31792161]
- [-4.7092036]
- [2.54629324]
- [3.39634
- [4.70833798]
- [4.21943738]
- [-3.46481252]
- [-4.70657762]
- [-0.37296535]
- [0.14072207]

```
[ 4.26372857]
[ 4.68691278]
[ 1.20068953]
[-4.92552407]
[ 0.61007361]
[ 3.98499229]
[ 2.98152954]
[ 4.09879831]
[ 4.92827865]
[-2.10621153]
[ 3.96988303]
[ 1.05428171]
[-1.58649877]
[ 2.41262391]
[-4.68382943]
[-3.00209887]
[ 2.17824054]
[ 4.62864372]
[-3.42174215]
[ 3.24110498]
[-4.59041032]
[-0.10349687]
[ 4.74605444]
[-4.81932749]
[ 2.84527302]
[-2.46052222]
[ 0.05968899]
[ 3.07686272]
[-1.19205355]
[-1.54193042]
[-4.46625195]
[-4.83257391]
[ 0.41097987]
[-4.00972237]
[ 2.56088925]
[ 3.2564741 ]]
```

1.1 A)

Estimate the value of the regression coefficients by using the analytical solution for the least squares estimation problem.

```
In [73]: time_start = time.clock()
    beta_ls_exact=np.dot(np.dot(np.linalg.inv(np.dot(np.transpose(X),X)),np.tr
    time_elapsed = (time.clock() - time_start)
    print('time elapsed=',time_elapsed)
    print(beta_ls_exact)
```

```
('time elapsed=', 0.0023641579900868237)
[[ 1.73944484]
[ 2.11849576]
[-3.3627126]
[ 2.49636401]
[-2.84054722]
[ 2.02156168]
[-2.86232325]
[ 0.35178602]
[ 1.543078 ]
 [ 3.75664986]
[-3.10144696]
[-0.49563234]
[ 4.07457553]
 [ 3.19734595]
[ 4.01312126]
[ 1.81554646]
[ 2.73727512]
[ 4.86453595]
[ 4.78753664]
[-2.28646111]
[-2.60981044]
[-4.13475238]
[-2.42150444]
 [ 4.51678882]
[-4.76576907]
[ 4.55297872]
 [ 4.76157291]
[-0.63205529]
[-4.11615598]
[ 1.24171108]
[-3.95975354]
[-1.08472859]
[-0.25454118]
[-2.45531301]
 [ 2.04235535]
[ 4.90231666]
[ 2.83335418]
[ 0.28134911]
 [ 4.84884805]
[ 0.42513108]
[-0.79616354]
[ 3.25057585]
[-1.57517965]
[ 0.0961234 ]
[ 2.17431404]
 [ 1.82505696]
```

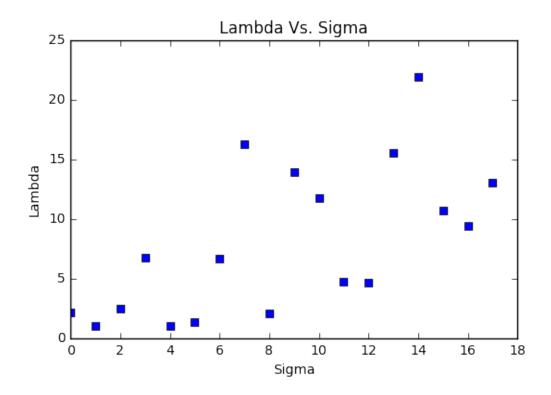
[4.22074613]

- [2.44749707]
- [-0.70609706]
- [-1.94542769]
- [4.95931038]
- [2.40542927]
- [-2.24506929]
- [4.64658585]
- [-2.99305659]
- [2.)) 3 0 3 0 3 0 3
- [-2.30420422]
- [-4.70322873]
- [2.55568737]
- [3.39306073]
- [4.69860549]
- [4.21740776]
- [-3.46522597]
- [-4.70731893]
- [-0.38375324]
- [0.15328952]
- [4.26222374]
- [4.69090512]
- [1.21393678]
- [-4.91855814]
- [0.60281507]
- [3.99072754]
- [2.98359187]
- [4.1058776]
- [4.92828094]
- [-2.10718704]
- [3.9875125]
- [1.06448384]
- [-1.58946094]
- [2.42858799]
- [-4.70019775]
- [-2.99818303]
- [2.16842197]
- [4.62660575]
- [-3.42353357]
- [3.24789051]
- [-4.59425366]
- [-0.09865654]
- [4.73365641]
- [-4.82251921]
- [2.85609984]
- [-2.43892912]
- [0.05248573]
- [3.066192]
- [-1.18456813]
- [-1.53919184]

```
[-4.4824774]
[-4.83151957]
[0.41117392]
[-4.02762808]
[2.57962647]
[3.24912254]]
```

1.2 B

```
In [76]: import matplotlib.pyplot as plt
         %matplotlib inline
         lambda_est=[]
         sigma=np.arange(1,10,0.5)
         for i in sigma :
             error=np.random.normal(0, i, (nsample,1)) # Normal random error with o
             Y=np.dot(X, beta)+error
             beta_ls_exact=np.dot(np.dot(np.linalg.inv(np.dot(np.transpose(X),X))),r
             lambda_est.append((np.linalg.norm(beta-beta_ls_exact,ord=2)/np.linalg
        print lambda_est
         plt.plot(lambda_est, 'bs')
         plt.xlabel('Sigma')
         plt.ylabel('Lambda')
         plt.title('Lambda Vs. Sigma')
         plt.show()
[2.0977724073092068, 1.0434809952479307, 2.4665810510725774, 6.714342056905366, 0.9
```



1.3 C)

Estimate the value of the regression coefficients (least squares) by using the tool minimize from the python package Scipy.optimize. Try at least three available solvers and compare their performance (iterations, function, gradient and hessian evaluations as well as total computational time).

```
In [77]: # c : Newton-CG
    from scipy.optimize import minimize

def least_sq_reg_der(beta_ls, X, Y):
        beta_ls=np.matrix(beta_ls)
        pp=-2*np.dot(np.transpose(Y-np.dot(X, np.transpose(beta_ls))), X)
        return np.squeeze(np.asarray(pp))

def least_sq_reg_hess(beta_ls, X, Y):
        return 2*np.dot(np.transpose(X), X)

        time_start = time.clock()
        res = minimize(least_sq_reg, beta_ls0, args=(X,Y), method = 'Newton-CG', jatime_elapsed = (time.clock() - time_start)
```

```
print('time elapsed=', time_elapsed)
        print(res.x)
        np.linalg.inv(least_sq_reg_hess(res.x,X,Y))
        print('error=', np.linalg.norm(np.transpose(beta_ls_exact)-res.x, ord=2)/np
Optimization terminated successfully.
        Current function value: 84919.433779
        Iterations: 13
        Function evaluations: 15
         Gradient evaluations: 27
        Hessian evaluations: 13
('time elapsed=', 0.01405822801461909)
\begin{bmatrix} -2.82008067 & 2.18757466 & -3.33272327 & 2.40049448 & -2.91963727 & 2.00327112 \end{bmatrix}
-2.92131844 \quad 0.38737346 \quad 1.41670753 \quad 3.80403476 \quad -3.04939229 \quad -0.58693961
 4.13023388 3.2712188 4.06065034 1.86865285 2.90094534 5.10282956
 4.75282604 \ -2.3773995 \ -2.74905144 \ -3.94538837 \ -2.45767374 \ \ 4.49870427
 -4.74963116 4.5581906 4.65647517 -0.59536712 -4.19275214 1.24511272
-3.89736906 -1.04011949 -0.2648055 -2.28654196 2.16801341 4.92252474
 2.94042701 0.53332892 4.79756196 0.43628567 -0.86060568 3.35301637
-1.41157385 0.06995832 2.14622713 1.82173066 4.29591559 2.45075603
 -0.63613901 \ -1.91125291 \ \ 4.94260168 \ \ 2.30714525 \ -2.39602297 \ \ 4.6346139
-3.05933576 -2.51372002 -4.71725957 2.5502426 3.42703598 4.78687509
  4.21202156 - 3.54248362 - 4.50429966 - 0.48099936 0.13159525 4.24485933
  4.77287047 1.38593122 -4.99300658 0.74922483 3.95908503 2.79126195
 3.99975694 4.84343316 -2.07182145 3.98490325 1.19556984 -1.65011529
 2.41928262 -4.77430334 -2.80623367 2.12898233 4.6608253 -3.45711524
 -2.4599172 0.12189708 2.88425646 -1.36533708 -1.58816479 -4.39826269
 -4.80547961 0.56007547 -3.78563627 2.50914512 3.304043311
('error=', 1.3659231966901152e-06)
In [78]: # c: dogleg
         from scipy.optimize import minimize
         def least_sq_reg_der(beta_ls, X, Y):
            beta_ls=np.matrix(beta_ls)
             pp=-2*np.dot(np.transpose(Y-np.dot(X,np.transpose(beta_ls))),X)
             return np.squeeze(np.asarray(pp))
         def least_sq_reg_hess(beta_ls, X, Y):
             return 2*np.dot(np.transpose(X),X)
        time_start = time.clock()
```

```
res = minimize(least_sq_reg, beta_ls0, args=(X,Y), method = 'dogleg', jac=1
        time_elapsed = (time.clock() - time_start)
        print('time elapsed=', time_elapsed)
        print (res.x)
        np.linalg.inv(least sq req hess(res.x, X, Y))
        print('error=', np.linalg.norm(np.transpose(beta_ls_exact)-res.x, ord=2)/np
Optimization terminated successfully.
        Current function value: 84919.433768
        Iterations: 6
        Function evaluations: 7
        Gradient evaluations: 7
        Hessian evaluations: 6
('time elapsed=', 0.008869112425600179)
[-2.82009166 \quad 2.18757262 \quad -3.33272408 \quad 2.40050035 \quad -2.91964431 \quad 2.00327309
-2.92131935 0.38737545 1.41670728 3.80403217 -3.04939149 -0.58693972
 4.13024247 3.27121943 4.06064646 1.86865365 2.9009471 5.1028255
  -4.74962366 4.55818668 4.65647563 -0.59536061 -4.19274504 1.24511478
-3.8973661 -1.04011885 -0.26481368 -2.28654173 2.16800687 4.92252054
 2.94043056 \quad 0.5333243 \quad 4.79756441 \quad 0.43627901 \quad -0.86060974 \quad 3.35301358
-1.41157203 0.06996948 2.14622611 1.8217317 4.29591723 2.45076112
 -0.63614187 -1.91125437 4.94259785 2.30714669 -2.39602395 4.63460325
 -3.05933115 -2.51371899 -4.71726272 2.55024272 3.42703614 4.7868769
 4.21201842 - 3.5424867 - 4.50429917 - 0.48099319 0.1316062 4.24485554
            1.38593473 -4.99300561 0.74922867 3.95908786 2.79126176
 4.7728776
 3.99975326 4.84343426 -2.07181554 3.98489739 1.19557716 -1.65011212
 2.41928082 \ -4.7743059 \ -2.80624142 \ 2.12898243 \ 4.66082827 \ -3.45711962
 3.31431908 - 4.59174474 - 0.0981666 4.70477382 - 4.95014286 2.87792284
-2.45991397 0.12189604 2.88425693 -1.36533547 -1.58816079 -4.39826434
 -4.8054921 0.56007872 -3.78564008 2.50915003 3.30404243]
('error=', 4.2990732639375794e-12)
In [79]: from scipy.optimize import minimize
        def least_sq_reg(beta_ls, X, Y):
            beta_ls=np.matrix(beta_ls)
            z=Y-X*np.transpose(beta_ls)
            return np.dot(np.transpose(z),z) #sum of the square errors, value of a
In [80]: # c :BFGS
        beta_ls0 = np.zeros(nvariables+1) #we need to initiate our initial point
        time_start = time.clock()
        res = minimize(least_sq_reg, beta_ls0, args=(X,Y), method = 'BFGS', option
        time_elapsed = (time.clock() - time_start)
        print('time elapsed=',time_elapsed)
```

```
print (res.x)
        print('error=', np.linalg.norm(np.transpose(beta_ls_exact)-res.x, ord=2)/np
Warning: Desired error not necessarily achieved due to precision loss.
         Current function value: 84919.433768
         Iterations: 131
        Function evaluations: 24515
         Gradient evaluations: 238
('time elapsed=', 1.4608064334461233)
[-2.8200985]
             2.18757251 -3.33272404 2.40050027 -2.9196443 2.00327308
-2.92131936 0.3873754 1.41670726 3.80403212 -3.04939138 -0.5869397
  4.13024253 3.27121944 4.0606465 1.86865365 2.90094716 5.10282556
 4.75282723 \ -2.3774021 \ -2.74905506 \ -3.94539385 \ -2.45767775 \ \ 4.49870628
-4.74962365 4.5581867 4.65647564 -0.59536055 -4.19274501 1.2451148
-3.89736611 -1.04011893 -0.2648137 -2.28654166 2.1680069 4.92252054
 2.94043061 0.53332426 4.79756441 0.43627895 -0.86060973 3.35301358
            0.06996955 2.14622612 1.82173174 4.29591722 2.45076115
 -1.411572
-0.63614186 -1.91125438 \ 4.94259787 \ 2.30714665 -2.39602388 \ 4.63460324
 -3.05933111 -2.51371897 -4.71726272 2.55024273 3.42703609 4.78687685
 4.2120184 -3.54248668 -4.50429913 -0.48099318 0.13160623 4.24485561
 4.77287762 1.38593473 -4.99300558 0.7492287
                                                3.95908792 2.79126178
 3.99975324 4.84343427 -2.07181555 3.98489735 1.19557716 -1.65011214
 2.41928088 - 4.77430592 - 2.80624141    2.12898241    4.66082837 - 3.45711963
 3.31431909 - 4.59174468 - 0.09816652  4.70477388 - 4.95014286  2.8779229
-2.45991397 0.12189603 2.8842569 -1.36533542 -1.58816079 -4.39826433
 -4.80549213 0.56007879 -3.78564002 2.50914997 3.30404246]
('error=', 2.1148376814635847e-07)
In [81]: # c :SLSQP
        beta_ls0 = np.zeros(nvariables+1) #we need to initiate our initial point
        time_start = time.clock()
         res = minimize(least_sq_reg, beta_ls0, args=(X,Y), method = 'SLSQP', optic
        time_elapsed = (time.clock() - time_start)
        print('time elapsed=', time_elapsed)
        print (res.x)
        print('error=', np.linalg.norm(np.transpose(beta_ls_exact)-res.x, ord=2)/np
Optimization terminated successfully.
                                       (Exit mode 0)
           Current function value: [[ 84919.43438612]]
           Iterations: 62
           Function evaluations: 6628
           Gradient evaluations: 62
('time elapsed=', 0.38456415182736237)
[-2.81999282 2.18757499 -3.33274337 2.40049986 -2.91964145 2.00328562
-2.92135673 0.38740984 1.41667548 3.8040489 -3.04938633 -0.58696508
  4.13026249 3.2712273 4.06064785 1.86863405 2.90094692 5.10280418
```

```
-4.7495816 4.55816327 4.65648354 -0.5953383 -4.19275952 1.24510698
-3.89736525 -1.04011663 -0.26475866 -2.28654486 2.16800036 4.92250585
 2.94045632 \quad 0.53331927 \quad 4.79756062 \quad 0.43632093 \quad -0.86062636 \quad 3.35304649
-1.41155463 0.07002751 2.14629284 1.82174526 4.29594552 2.45075327
 -0.63611914 -1.9112522 4.94254981 2.3071427 -2.39602753 4.63456411
-3.05933373 -2.51372557 -4.71728558 2.55019751 3.42705259 4.78684688
 4.21203778 \ -3.54249077 \ -4.50430907 \ -0.48098153 \ \ 0.13159908 \ \ 4.24482322
 4.77287968 1.38597311 -4.99303748 0.74922122 3.95905633 2.79125096
 3.99978166 4.84342029 -2.07179286 3.98486089 1.19553417 -1.6501765
 2.41921376 \ -4.77430548 \ -2.80619574 \ \ 2.12901886 \ \ 4.66084734 \ -3.45709624
 3.31433304 - 4.59175443 - 0.09815162  4.70480099 - 4.95015551  2.87791769
-2.45999135 0.12189591 2.88425535 -1.36529894 -1.58814319 -4.39827985
-4.80542618 0.56006648 -3.78563869 2.50912917 3.30408075]
('error=', 9.0791862297303001e-06)
In [82]: # c : CG
         beta_ls0 = np.zeros(nvariables+1) #we need to initiate our initial point
         time start = time.clock()
         res = minimize(least_sq_reg, beta_ls0, args=(X,Y), method = 'CG', options
         time_elapsed = (time.clock() - time_start)
         print('time elapsed=',time_elapsed)
         print (res.x)
         print('error=', np.linalg.norm(np.transpose(beta_ls_exact)-res.x, ord=2)/np
Warning: Desired error not necessarily achieved due to precision loss.
         Current function value: 84919.438062
         Iterations: 243
         Function evaluations: 55632
         Gradient evaluations: 540
('time elapsed=', 2.9277961149491603)
[-2.85789181 \quad 2.1876595 \quad -3.33265676 \quad 2.40058637 \quad -2.91958424 \quad 2.0033621
-2.92124797 0.38743794 1.41677483 3.8040492 -3.04932774 -0.58686475
 4.13034603 3.27131329 4.06073374 1.86871524 2.90101457 5.10290849
  4.75291173 -2.37733101 -2.74897404 -3.94534963 -2.45755214 4.4987615
-4.74954624 4.55825218 4.65654622 -0.59529921 -4.19269757 1.24517746
-3.89728324 -1.04006126 -0.26472422 -2.28641039 2.16808449 4.92261235
 2.94051853 0.5333913 4.7976289 0.43632826 -0.86052493 3.35309622
-1.41149609 0.07004405 2.14633029 1.8218001 4.2959728 2.45083466
-0.63607714 \ -1.91116057 \ \ 4.94266668 \ \ \ 2.30720999 \ \ -2.39592101 \ \ \ 4.63465029
-3.05928473 -2.5136702 -4.7171507 2.5503713 3.42710086 4.78695988
 4.21207411 -3.54236985 -4.50420913 -0.48090851 0.13170382 4.24491855
 4.77296519 1.3860117 -4.99294112 0.74922996 3.95915735 2.79134114
 3.99980412 4.84347789 -2.0717737 3.98497698 1.19565988 -1.65003571
 2.41931526 -4.77427489 -2.80616743 2.12906819 4.66091626 -3.45704269
  3.3143886 - 4.59171885 - 0.09806332  4.70488323 - 4.95006486  2.87796457
```

4.75279975 -2.37740227 -2.74908372 -3.94539617 -2.45771762 4.49873764

```
-2.45985323 0.12197447 2.88435942 -1.36521473 -1.58804764 -4.39818139
              0.56020827 -3.78554284 2.50927804 3.30413515]
-4.8054392
('error=', 0.0011659627184107803)
In [4]: import sympy
        from pandas import DataFrame
        from sympy import *
        # For Final report we need to put 'Current function value', 'Iteration', 'Fu
        ### Fill value instead of 1 2 3 .....
        t = [[84919.433779, 13, 15, 27, 13, 0.014, 1.37e-6], #Newton-CG
             [84919.434768 , 6, 7 ,7 ,6 , 0.0089 ,4.30e-12 ], #dogleg
             [84919.433758 , 131,24515 ,238 ,"NA" ,1.46 ,2.11e-7 ], #BFGS
             [84919.434386 ,62 ,6628 ,62 ,"NA" ,0.38 ,9.08e-6 ], #SLSQP
             [84919.438062 ,243 ,55632 ,540 ,"NA" ,2.93 ,0.0012 ]] #CG
        table = DataFrame(t, index=['Newton-CG', 'dogleg', 'BFGS', 'SLSQP', 'CG'],
        table
Out[4]:
                   Current function value Iteration Function evaluations
        Newton-CG
                             84919.433779
                                                   13
                                                                         15
                             84919.434768
        dogleg
                                                    6
                                                                          7
        BFGS
                             84919.433758
                                                  131
                                                                      24515
        SLSQP
                             84919.434386
                                                  62
                                                                       6628
        CG
                             84919.438062
                                                  243
                                                                      55632
                   Gradient evaluations Hessian evaluations
                                                              Time elapsed \
                                                                    0.0140
        Newton-CG
                                     27
                                                          13
        dogleg
                                      7
                                                           6
                                                                    0.0089
                                    238
        BFGS
                                                          NA
                                                                    1.4600
        SLSQP
                                     62
                                                                    0.3800
                                                          NA
                                    540
                                                                    2.9300
        CG
                                                          NA
                          Error
        Newton-CG 1.370000e-06
                   4.300000e-12
        dogleg
        BFGS
                   2.110000e-07
        SLSQP
                   9.080000e-06
        CG
                   1.200000e-03
```

1.4 D)

Considering again the least squares estimation problem, estimate the value of the regression coefficients by implementing the:

- i. Gradient method
- ii. Newton method
- iii. Quasi-Newton method

Consider a like search technique to improve the algorithm convergence, e.x., Armijo rule. Compare the performance of these algorithms (iterations, function, gradient and hessian evaluations as well as total computational time).

```
In [84]: #definitinition of OF #objective function
    def least_sq_reg(beta_ls, X, Y):
        beta_ls=np.matrix(beta_ls)
        z=Y-X*np.transpose(beta_ls)
        return np.transpose(z)*z

#definition of Gradient

def least_sq_reg_der(beta_ls,X,Y):
        beta_ls=np.matrix(beta_ls)
        pp=-2*np.transpose(Y-X*np.transpose(beta_ls))*X
        aa= np.squeeze(np.asarray(pp))
        return aa

#definition of hessian
    def least_sq_reg_hess(beta_ls,X,Y):
        ss=2*np.dot(np.transpose(X),X)
        return ss
```

1.5 i) Gradient method

- \rightarrow From an initial iterate x_0
 - \rightarrow Compute search (descent) directions p_k
 - \rightarrow Far from the solution, compute a steplength $\alpha_k > 0$
 - \rightarrow Movement:

$$x_{k+1} = x_k + \alpha_k p_k$$

Until convergence to a local solution

```
time_start = time.clock()
        while (i <= n_iter-2) and (tol>epsilon):
             grad=least_sq_reg_der(beta_lsg, X, Y) #this function gives us the value
             ddirect=-grad
             #########################
                  Armijo Rule
             sigma=0.1
            beta=0.5
            alpha=1
            while (least_sq_reg(beta_lsg+alpha*ddirect, X, Y) > least_sq_reg(beta_lsg
                 alpha=alpha*beta
             ###########################
            beta_lsg=beta_lsg+alpha*ddirect
            OF_iter[i]=least_sq_reg(beta_lsg,X,Y) # Objective Function ---Residua.
            tol=np.linalg.norm(grad, ord=2)
            tol_iter[i]=tol
         time elapsed = (time.clock() - time start)
        print('time elapsed=',time_elapsed)
        print('iterations',i)
        print (OF_iter[i])
        print (beta_lsg)
        print (np.transpose (beta_ls_exact))
        print('Tolerance=',tol)
        print('error=', np.linalg.norm(np.transpose(beta_ls_exact)-beta_lsg, ord=2)/
('time elapsed=', 215.57388964362326)
('iterations', 99999)
84929.3073365
[-1.00552324 \quad 2.18336177 \quad -3.33600171 \quad 2.39643687 \quad -2.92246059 \quad 1.99875166
-2.92468279 0.38429239 1.41333943 3.80317979 -3.05248791 -0.59071866
  4.12524893 3.26656723 4.05649917 1.86564815 2.8978303 5.09889964
  -4.75297247 4.55537918 4.65282515 -0.59800657 -4.19509426 1.24210405
-3.90135134 -1.04271539 -0.26901538 -2.29302437 2.16423839 4.91800017
 2.93592439 0.53012202 4.79433681 0.43390435 -0.86465576 3.34852329
-1.41526794 0.06632625 2.14111084 1.81840842 4.29306879 2.44703809
 -0.63913949 -1.91576422 4.93924581 2.30399171 -2.40088197 4.63240874
 -3.06169684 -2.5159778 -4.72248466 2.54384261 3.42392076 4.7828991
  4.20934812 - 3.54783455 - 4.50863292 - 0.48497834 0.1268127
                                                             4.24195353
 4.76853478 1.38218161 -4.99625161 0.74897886 3.95538557 2.78762389
 3.99727475 4.84105212 -2.0735365 3.98123654 1.19165168 -1.65348411
 2.41727442 \quad -4.77572941 \quad -2.80935509 \quad 2.12472609 \quad 4.65639364 \quad -3.46088663
 3.31067667 - 4.59263375 - 0.10338909   4.6996278   -4.95383034   2.87600641
 -2.46276516 0.11816647 2.87931377 -1.37122449 -1.59362318 -4.40189991
 -4.80763108 0.55374605 -3.79003875 2.50319568 3.29974066]
```

```
-2.92131935 0.38737545 1.41670728 3.80403217 -3.04939149 -0.58693972
  4.13024247 3.27121943 4.06064646 1.86865365 2.9009471 5.1028255
  -4.74962366 4.55818668 4.65647563 -0.59536061 -4.19274504 1.24511478
 -3.8973661 -1.04011885 -0.26481368 -2.28654173 2.16800687 4.92252054
  2.94043056 0.5333243 4.79756441 0.43627901 -0.86060974 3.35301358
 -1.41157203 0.06996948 2.14622611 1.8217317
                                           4.29591723 2.45076112
 -0.63614187 -1.91125437 4.94259785 2.30714669 -2.39602395 4.63460325
 -3.05933115 -2.51371899 -4.71726272 2.55024272 3.42703614 4.7868769
  4.21201842 \ -3.5424867 \ -4.50429917 \ -0.48099319 \ 0.1316062 \ 4.24485554
  3.99975326 4.84343426 -2.07181554 3.98489739 1.19557716 -1.65011212
  2.41928082 - 4.7743059 - 2.80624142 2.12898243 4.66082827 - 3.45711962
  -2.45991397 0.12189604 2.88425693 -1.36533547 -1.58816079 -4.39826434
 -4.8054921 0.56007872 -3.78564008 2.50915003 3.30404243]]
('Tolerance=', 11.957228882608536)
('error=', 0.056169323979137355)
In [98]: ### Without Armijo Rule
       (a,b) = X. shape
       beta lsg=np.zeros(b) #initial value for beta
       alpha= 0.0000001
       n iter=100000 #maximim number iteration
       OF_iter=np.zeros(n_iter)
       tol_iter=np.zeros(n_iter)
       alpha_iter=np.zeros(n_iter)
       i=0;
       tol=1000; # Tolerance
       epsilon=1e-3;
       time_start = time.clock()
       while (i <= n_iter-2) and (tol>epsilon):
           grad=least_sq_reg_der(beta_lsg, X, Y) #this function gives us the value
           ddirect=-grad
          beta lsg=beta lsg+alpha*ddirect
           OF_iter[i]=least_sq_reg(beta_lsg,X,Y) # Objective Function ---Residua.
           tol=np.linalg.norm(grad,ord=2)
           tol_iter[i]=tol
       time_elapsed = (time.clock() - time_start)
       print('time elapsed=',time_elapsed)
       print('iterations',i)
       print (OF_iter[i])
```

```
print (beta_lsq)
         print (np.transpose (beta_ls_exact))
         print('Tolerance=',tol)
         print('error=', np.linalg.norm(np.transpose(beta_ls_exact)-beta_lsg, ord=2)/
('time elapsed=', 14.0880259515543)
('iterations', 99999)
84942.527301
              2.18113141 -3.33773806 2.39428447 -2.92395271 1.99635687
[-0.0449488
-2.92646459 0.38265903 1.41155527 3.80272724 -3.05412837 -0.59272041
  4.12260421 3.26410322 4.05430245 1.86405585 2.89617906 5.09682015
  4.74621892 -2.38243967 -2.75448725 -3.94850098 -2.46658356 4.49459399
-4.75474652 4.55389168 4.65089142 -0.59940854 -4.19633916 1.24050891
-3.90346229 -1.04409118 -0.27124091 -2.29645735 2.16224217 4.91560592
 2.93353771 0.52842552 4.79262692 0.43264598 -0.86679887 3.34614498
-1.41722575 0.06439638 2.13840169 1.8166479 4.29155963 2.44506596
 -0.64072767 -1.91815287 4.93747005 2.30232025 -2.40345492 4.63124573
-3.06295048 -2.51717478 -4.72525025 2.54045333 3.4222703 4.78079204
 4.20793326 - 3.55066681 - 4.51092836 - 0.48708925 0.12427388 4.240416
 4.76623454 1.38019354 -4.99797124 0.74884532 3.95342441 2.78569681
 3.99596141 4.83978978 -2.07444881 3.9792973
                                                 1.18957239 -1.65527045
 2.41621101 \;\; -4.77648427 \;\; -2.81100466 \quad \  \  2.1224716 \qquad \  \  4.65404478 \;\; -3.46288209
 3.30874722 - 4.59310568 - 0.106155 4.69690238 - 4.95578365 2.87499064
-2.46427576 0.11619089 2.87669574 -1.37434324 -1.59651609 -4.40382578
-4.80876468 0.55039243 -3.7923686 2.50004233 3.29746211
[[-2.82009166 2.18757262 -3.33272408 2.40050035 -2.91964431
                                                               2.00327309
 -2.92131935 0.38737545 1.41670728 3.80403217 -3.04939149 -0.58693972
   4.13024247 3.27121943 4.06064646 1.86865365 2.9009471
                                                               5.1028255
   4.75282718 -2.37740208 -2.74905513 -3.94539386 -2.45767779 4.49870622
 -4.74962366 4.55818668 4.65647563 -0.59536061 -4.19274504 1.24511478
 -3.8973661 -1.04011885 -0.26481368 -2.28654173 2.16800687 4.92252054
  2.94043056 \quad 0.5333243 \quad 4.79756441 \quad 0.43627901 \quad -0.86060974 \quad 3.35301358
 -1.41157203 0.06996948 2.14622611 1.8217317
                                                   4.29591723 2.45076112
 -0.63614187 -1.91125437 4.94259785 2.30714669 -2.39602395 4.63460325
 -3.05933115 -2.51371899 -4.71726272 2.55024272 3.42703614 4.7868769
   4.21201842 - 3.5424867 - 4.50429917 - 0.48099319 0.1316062
                                                               4.24485554
   4.7728776
               1.38593473 - 4.99300561 \quad 0.74922867 \quad 3.95908786 \quad 2.79126176
   3.99975326 4.84343426 -2.07181554 3.98489739 1.19557716 -1.65011212
   2.41928082 - 4.7743059 - 2.80624142 2.12898243 4.66082827 - 3.45711962
   3.31431908 - 4.59174474 - 0.0981666 4.70477382 - 4.95014286 2.87792284
 -2.45991397 0.12189604 2.88425693 -1.36533547 -1.58816079 -4.39826434
  -4.8054921
               0.56007872 -3.78564008 2.50915003 3.30404243]]
('Tolerance=', 16.639447266111439)
('error=', 0.085955155074071907)
```

In []:

1.6 ii) Newtons method

- \rightarrow From an initial iterate x_0
- \rightarrow Compute search (descent) directions $p_k = -(\nabla^2 f(x_k))^{-1} \nabla f(x_k)$, whenever $\nabla^2 f(x_k)$ is non-singular.
 - \rightarrow Far from the solution, compute a steplength $\alpha_k > 0$
 - \rightarrow Movement:

$$x_{k+1} = x_k + \alpha_k p_k$$

Until convergence to a local solution

```
In [99]: ### With Armijo Rule
         (a,b) = X. shape
         beta_lsg=np.zeros(b) #initial value for beta
         #alpha= 0.0000001
         n_iter=100000 #maximim number iteration
         OF_iter=np.zeros(n_iter)
         tol_iter=np.zeros(n_iter)
         alpha_iter=np.zeros(n_iter)
         i=0;
         tol=1000; # Tolerance
         epsilon=1e-3;
         time_start = time.clock()
         while (i <= n_iter-2) and (tol>epsilon):
             i=i+1
             grad=least_sq_reg_der(beta_lsg, X, Y)
             hess=least_sq_reg_hess(beta_lsg,X,Y) #this function gives us the value
             ddirect=- (np.dot (np.linalg.inv(hess), grad))
             #########################
                   Armijo Rule
             sigma=0.1
             beta=0.5
             alpha=1
             while (least_sq_reg(beta_lsg+alpha*ddirect, X, Y) > least_sq_reg(beta_lsg
                 alpha=alpha*beta
             ##########################
             beta_lsq=beta_lsq+alpha*ddirect
             OF_iter[i]=least_sq_reg(beta_lsq,X,Y)
             tol=np.linalg.norm(hess,ord=2)
             tol_iter[i]=tol
         time_elapsed = (time.clock() - time_start)
         print('time elapsed=',time_elapsed)
         print('iterations',i)
         print(OF_iter[i])
         print (beta_lsg)
```

print (np.transpose (beta_ls_exact))

```
print('Tolerance=',tol)
       print('error=', np.linalg.norm(np.transpose(beta_ls_exact)-beta_lsg, ord=2)/
('time elapsed=', 293.5455931344186)
('iterations', 99999)
84919.4337684
[-2.82009166 \quad 2.18757262 \quad -3.33272408 \quad 2.40050035 \quad -2.91964431 \quad 2.00327309
-2.92131935 0.38737545 1.41670728 3.80403217 -3.04939149 -0.58693972
 4.13024247 3.27121943 4.06064646 1.86865365 2.9009471 5.1028255
 -4.74962366 4.55818668 4.65647563 -0.59536061 -4.19274504 1.24511478
-3.8973661 -1.04011885 -0.26481368 -2.28654173 2.16800687 4.92252054
 2.94043056 0.5333243 4.79756441 0.43627901 -0.86060974 3.35301358
-1.41157203 0.06996948 2.14622611 1.8217317
                                           4.29591723 2.45076112
-0.63614187 -1.91125437 4.94259785 2.30714669 -2.39602395 4.63460325
-3.05933115 -2.51371899 -4.71726272 2.55024272 3.42703614 4.7868769
 4.21201842 - 3.5424867 - 4.50429917 - 0.48099319 0.1316062
                                                      4.24485554
 3.99975326 4.84343426 -2.07181554 3.98489739 1.19557716 -1.65011212
 2.41928082 \ -4.7743059 \ -2.80624142 \ 2.12898243 \ 4.66082827 \ -3.45711962
 -2.45991397 0.12189604 2.88425693 -1.36533547 -1.58816079 -4.39826434
-4.8054921 0.56007872 -3.78564008 2.50915003 3.304042431
-2.92131935 0.38737545 1.41670728 3.80403217 -3.04939149 -0.58693972
  4.13024247 3.27121943 4.06064646 1.86865365 2.9009471 5.1028255
  4.75282718 -2.37740208 -2.74905513 -3.94539386 -2.45767779 4.49870622
 -4.74962366 4.55818668 4.65647563 -0.59536061 -4.19274504 1.24511478
 -3.8973661 -1.04011885 -0.26481368 -2.28654173 2.16800687 4.92252054
  2.94043056 0.5333243 4.79756441 0.43627901 -0.86060974 3.35301358
 -1.41157203 0.06996948 2.14622611 1.8217317
                                            4.29591723 2.45076112
 -0.63614187 -1.91125437 4.94259785 2.30714669 -2.39602395 4.63460325
 -3.05933115 -2.51371899 -4.71726272 2.55024272 3.42703614 4.7868769
  4.21201842 - 3.5424867 - 4.50429917 - 0.48099319 0.1316062
                                                        4.24485554
  4.7728776
            1.38593473 -4.99300561 0.74922867 3.95908786 2.79126176
  3.99975326 4.84343426 -2.07181554 3.98489739 1.19557716 -1.65011212
  2.41928082 \ -4.7743059 \ -2.80624142 \ 2.12898243 \ 4.66082827 \ -3.45711962
  3.31431908 - 4.59174474 - 0.0981666  4.70477382 - 4.95014286  2.87792284
 -2.45991397 0.12189604 2.88425693 -1.36533547 -1.58816079 -4.39826434
            0.56007872 -3.78564008 2.50915003 3.30404243]]
 -4.8054921
('Tolerance=', 4972171.1853834139)
('error=', 4.2435594497630421e-12)
In [100]: ### Without Armijo Rule
         (a,b) = X.shape
        beta_lsg=np.zeros(b) #initial value for beta
```

```
alpha= 0.0000001
           n_iter=100000 #maximim number iteration
           OF_iter=np.zeros(n_iter)
           tol_iter=np.zeros(n_iter)
           alpha_iter=np.zeros(n_iter)
           i=0;
           tol=1000; # Tolerance
           epsilon=1e-3;
           time_start = time.clock()
           while (i <= n_iter-2) and (tol>epsilon):
               grad=least_sq_reg_der(beta_lsg, X, Y)
               hess=least_sq_reg_hess(beta_lsg,X,Y) #this function gives us the value
               ddirect=-(np.dot(np.linalg.inv(hess), grad))
               beta_lsg=beta_lsg+alpha*ddirect
               OF_iter[i]=least_sq_reg(beta_lsg,X,Y)
               tol=np.linalg.norm(hess,ord=2)
               tol_iter[i]=tol
           time_elapsed = (time.clock() - time_start)
           print('time elapsed=',time_elapsed)
           print('iterations',i)
           print(OF_iter[i])
           print (beta_lsg)
           print (np.transpose (beta_ls_exact))
           print('Tolerance=',tol)
           print('error=', np.linalg.norm(np.transpose(beta_ls_exact)-beta_lsg, ord=2)
('time elapsed=', 192.15463624136464)
('iterations', 99999)
84611989.3714
\begin{bmatrix} -0.0280601 & 0.0217665 & -0.03316083 & 0.02388514 & -0.02905066 & 0.0199327 \end{bmatrix}
 -0.02906733 0.00385441 0.01409633 0.03785038 -0.03034165 -0.00584009
  0.04109619 \quad 0.03254885 \quad 0.04040371 \quad 0.01859323 \quad 0.02886462 \quad 0.05077346
  0.04729095 \ -0.02365531 \ -0.02735328 \ -0.03925694 \ -0.02445406 \ \ 0.04476243
 -0.04725908 \quad 0.04535427 \quad 0.04633225 \quad -0.00592388 \quad -0.0417181 \quad 0.01238898
 -0.03877906 -0.01034925 -0.00263491 -0.02275125 0.02157182 0.04897941
  0.02925748 \quad 0.00530661 \quad 0.04773609 \quad 0.00434101 \quad -0.00856313 \quad 0.03336271
 -0.01404524 0.0006962 0.0213551 0.01812635 0.04274467 0.02438524
 -0.00632965 -0.01901711 0.04917918 0.02295627 -0.0238406 0.04611462
 -0.03044055 -0.02501167 -0.04693708 0.02537509 0.03409924 0.04762975
  0.04190987 - 0.03524798 - 0.04481808 - 0.00478591 0.00130949 0.0422366
  0.04749046 \quad 0.01379014 \quad -0.04968074 \quad 0.00745488 \quad 0.03939319 \quad 0.02777324
  0.03979782 0.0481925 -0.02061471 0.03965
                                                      0.01189607 -0.01641873
  0.02407201 \ -0.04750467 \ -0.02792229 \ \ 0.02118352 \ \ 0.04637556 \ -0.03439857
  0.0329777 \quad -0.04568817 \quad -0.00097676 \quad 0.04681282 \quad -0.04925426 \quad 0.02863553
 -0.02447631 \quad 0.00121287 \quad 0.02869855 \quad -0.01358518 \quad -0.01580231 \quad -0.04376303
```

```
-0.04781497 0.00557282 -0.03766738 0.02496621 0.03287545
-2.92131935 0.38737545 1.41670728 3.80403217 -3.04939149 -0.58693972
  4.13024247 3.27121943 4.06064646 1.86865365 2.9009471
                                                         5.1028255
  4.75282718 -2.37740208 -2.74905513 -3.94539386 -2.45767779 4.49870622
 -4.74962366 4.55818668 4.65647563 -0.59536061 -4.19274504 1.24511478
 -3.8973661 -1.04011885 -0.26481368 -2.28654173 2.16800687 4.92252054
  2.94043056 0.5333243 4.79756441 0.43627901 -0.86060974 3.35301358
 -1.41157203 0.06996948 2.14622611 1.8217317 4.29591723 2.45076112
 -0.63614187 -1.91125437 4.94259785 2.30714669 -2.39602395 4.63460325
 -3.05933115 -2.51371899 -4.71726272 2.55024272 3.42703614 4.7868769
  4.21201842 - 3.5424867 - 4.50429917 - 0.48099319 0.1316062 4.24485554
            1.38593473 -4.99300561 0.74922867 3.95908786 2.79126176
  4.7728776
  3.99975326 4.84343426 -2.07181554 3.98489739 1.19557716 -1.65011212
  2.41928082 \ -4.7743059 \ -2.80624142 \ 2.12898243 \ 4.66082827 \ -3.45711962
  3.31431908 - 4.59174474 - 0.0981666 4.70477382 - 4.95014286 2.87792284
 -2.45991397 0.12189604 2.88425693 -1.36533547 -1.58816079 -4.39826434
 -4.8054921 0.56007872 -3.78564008 2.50915003 3.3040424311
('Tolerance=', 4972171.1853834139)
('error=', 99.501828333603413)
```

1.7 iii) Quasi-Newton method

```
In [101]: ### With Armijo Rule
          (a,b) = X \cdot shape
          beta_quasi=np.zeros(b) #initial value for beta
          #alpha= 0.0000001
          n_iter=100000 #maximim number iteration
          OF_iter=np.zeros(n_iter)
          tol_iter=np.zeros(n_iter)
          alpha_iter=np.zeros(n_iter)
          i=0;
          tol=1000; # Tolerance
          epsilon=1e-5;
          time start = time.clock()
          while (i <= n_iter-2) and (tol>epsilon):
              grad=least_sq_reg_der(beta_quasi, X, Y)
              if (i==1):
                  grad=least_sq_reg_der(beta_quasi,X,Y)
                  B=least_sq_req_hess(beta_quasi, X, Y)
              else:
```

```
grad=least_sq_reg_der(beta_quasi, X, Y)
                 y= grad - grad_previous
                 s= beta_quasi - beta_quasi_previous
                 a=np.dot(B, s)
                 b=np.transpose(np.dot(B, s))
                 c=np.dot(np.dot(np.transpose(s), B), s)
                 d=np.dot(y, np.transpose(y))
                 e=np.dot(np.transpose(y), s)
                 ### Page 44 Formulas
                 B = B + np.dot(y-a, np.transpose(y-a))/np.dot(np.transpose(y-a),s)
                 \# B= B - (np.dot(a,b)/c) + (d/e) (BFGS Formula)
             ddirect=-(np.dot(np.linalg.inv(B), grad))
             ###########################
                  Armijo Rule
             sigma=0.1
             beta=0.5
             alpha=1
             while (least_sq_reg(beta_quasi+alpha*ddirect, X, Y) > least_sq_reg(beta_
                 alpha=alpha*beta
             ##########################
             beta_quasi_previous= beta_quasi
             beta_quasi=beta_quasi_previous + alpha*ddirect
             OF_iter[i]=least_sq_reg(beta_quasi,X,Y)
             tol=np.linalg.norm(grad,ord=2)
             tol_iter[i]=tol
         time_elapsed = (time.clock() - time_start)
         print('time elapsed=',time_elapsed)
         print('iterations',i)
         print(OF_iter[i])
         print(beta quasi)
         print (np.transpose (beta_ls_exact))
         print('Tolerance=',tol)
         print('error=', np.linalg.norm(np.transpose(beta_ls_exact)-beta_quasi, ord=
('time elapsed=', 0.0035460236395010725)
('iterations', 2)
84919.4337684
[-2.82009166 \ 2.18757262 \ -3.33272408 \ 2.40050035 \ -2.91964431 \ 2.00327309
-2.92131935 0.38737545 1.41670728 3.80403217 -3.04939149 -0.58693972
 4.13024247 3.27121943 4.06064646 1.86865365 2.9009471 5.1028255
  -4.74962366 4.55818668 4.65647563 -0.59536061 -4.19274504 1.24511478
 -3.8973661 -1.04011885 -0.26481368 -2.28654173 2.16800687 4.92252054
```

grad_previous=grad

```
2.94043056 0.5333243 4.79756441 0.43627901 -0.86060974 3.35301358
-1.41157203 0.06996948 2.14622611 1.8217317 4.29591723 2.45076112
-0.63614187 -1.91125437 4.94259785 2.30714669 -2.39602395 4.63460325
-3.05933115 -2.51371899 -4.71726272 2.55024272 3.42703614 4.7868769
 4.21201842 - 3.5424867 - 4.50429917 - 0.48099319 0.1316062 4.24485554
 4.7728776
           1.38593473 -4.99300561 0.74922867 3.95908786 2.79126176
 3.99975326 4.84343426 -2.07181554 3.98489739 1.19557716 -1.65011212
 2.41928082 \ -4.7743059 \ -2.80624142 \ 2.12898243 \ 4.66082827 \ -3.45711962
 3.31431908 - 4.59174474 - 0.0981666 4.70477382 - 4.95014286 2.87792284
-2.45991397 0.12189604 2.88425693 -1.36533547 -1.58816079 -4.39826434
-4.8054921 0.56007872 -3.78564008 2.50915003 3.30404243]
-2.92131935 \quad 0.38737545 \quad 1.41670728 \quad 3.80403217 \quad -3.04939149 \quad -0.58693972
  4.13024247 3.27121943 4.06064646 1.86865365 2.9009471 5.1028255
  -4.74962366 4.55818668 4.65647563 -0.59536061 -4.19274504 1.24511478
 -3.8973661 -1.04011885 -0.26481368 -2.28654173 2.16800687 4.92252054
  2.94043056 0.5333243 4.79756441 0.43627901 -0.86060974 3.35301358
 -1.41157203 0.06996948 2.14622611 1.8217317
                                              4.29591723 2.45076112
 -0.63614187 -1.91125437 4.94259785 2.30714669 -2.39602395 4.63460325
 -3.05933115 -2.51371899 -4.71726272 2.55024272 3.42703614 4.7868769
  4.21201842 -3.5424867 -4.50429917 -0.48099319 0.1316062
                                                         4.24485554
  4.7728776 1.38593473 -4.99300561 0.74922867 3.95908786 2.79126176
  3.99975326 4.84343426 -2.07181554 3.98489739 1.19557716 -1.65011212
  2.41928082 - 4.7743059 - 2.80624142 2.12898243 4.66082827 - 3.45711962
  3.31431908 -4.59174474 -0.0981666
                                  4.70477382 -4.95014286 2.87792284
 -2.45991397 0.12189604 2.88425693 -1.36533547 -1.58816079 -4.39826434
             0.56007872 -3.78564008 2.50915003 3.30404243]]
 -4.8054921
('Tolerance=', 2.987721920840585e-06)
('error=', 6.429578978306502e-13)
```

In [102]: ### Without Armijo Rule

```
(a,b)=X.shape
beta_quasi=np.zeros(b) #initial value for beta
alpha= 0.0000001
n_iter=100000 #maximim number iteration
OF_iter=np.zeros(n_iter)
tol_iter=np.zeros(n_iter)
alpha_iter=np.zeros(n_iter)
i=0;
tol=1000; # Tolerance
epsilon=1e-5;
```

```
while (i <= n_iter-2) and (tol>epsilon):
              i=i+1
              grad=least_sq_reg_der(beta_quasi, X, Y)
              if (i==1):
                   grad=least_sq_reg_der(beta_quasi, X, Y)
                  B=least_sq_reg_hess(beta_quasi, X, Y)
              else:
                  grad_previous=grad
                   grad=least_sq_reg_der(beta_quasi, X, Y)
                  y= grad - grad_previous
                  s= beta_quasi - beta_quasi_previous
                  a=np.dot(B, s)
                  b=np.transpose(np.dot(B, s))
                  c=np.dot(np.dot(np.transpose(s), B), s)
                  d=np.dot(y, np.transpose(y))
                  e=np.dot(np.transpose(y), s)
                   ### Page 44 Formulas
                  B = B + np.dot(y-a, np.transpose(y-a))/np.dot(np.transpose(y-a),s)
                   \# B= B - (np.dot(a,b)/c) + (d/e) (BFGS Formula)
              ddirect=-(np.dot(np.linalg.inv(B), grad))
              beta_quasi_previous= beta_quasi
              beta_quasi=beta_quasi_previous + alpha*ddirect
              OF_iter[i]=least_sq_reg(beta_quasi,X,Y)
              tol=np.linalg.norm(grad,ord=2)
              tol_iter[i]=tol
          time_elapsed = (time.clock() - time_start)
          print('time elapsed=',time_elapsed)
          print('iterations',i)
          print(OF_iter[i])
          print (beta_quasi)
          print (np.transpose (beta_ls_exact))
          print('Tolerance=',tol)
          print('error=', np.linalg.norm(np.transpose(beta_ls_exact)-beta_quasi, ord=
('time elapsed=', 77.44199172950175)
('iterations', 99999)
84612255.8376
[-0.69455439 \quad 0.02330877 \quad -0.03196133 \quad 0.02538503 \quad -0.02802235 \quad 0.02159238
-0.02782555 0.00498215 0.01533958 0.03817249 -0.0292014 -0.00445133
  0.04292589 0.03425616 0.04192465 0.01969262 0.03000818 0.05220902
  0.04888016 \ -0.02244421 \ -0.02604743 \ -0.0385179 \ -0.02231664 \ 0.04574423
```

time_start = time.clock()

```
-0.04602987 0.04638269 0.04767248 -0.00495406 -0.04085386 0.01351047
-0.03731758 \ -0.00940024 \ -0.00109407 \ -0.02037651 \ \ 0.02295996 \ \ 0.05064143
 0.03090196 0.00648642 0.04892168 0.0052158 -0.00708273 0.03500935
-0.01268554 0.00202509 0.02323332 0.01934208 0.04378862 0.02574653
-0.00521638 -0.01736145 0.05041185 0.02412116 -0.02206341 0.04692197
-0.02956954 -0.0241941 -0.0450268 0.02771753 0.03523912 0.04909869
 0.04288969 - 0.03328658 - 0.04322499 - 0.00332134  0.00306589  0.04330142
 0.04908182 \quad 0.01516352 \quad -0.04848864 \quad 0.00754634 \quad 0.04075071 \quad 0.02911294
 0.04070567 0.04907051 -0.01998648 0.04099637 0.01332996 -0.01517363
 0.0248067 \quad -0.04697969 \quad -0.02677797 \quad 0.02275512 \quad 0.04800963 \quad -0.03300447
 0.0343062 \quad -0.04535301 \quad 0.00093947 \quad 0.04869848 \quad -0.04790353 \quad 0.02933167
-0.02343911 0.00257443 0.03050908 -0.0114265 -0.0137986 -0.04242246
-0.04702582 0.00790206 -0.03604466 0.02715162 0.03446269
-2.92131935 \quad 0.38737545 \quad 1.41670728 \quad 3.80403217 \quad -3.04939149 \quad -0.58693972
  4.13024247 3.27121943 4.06064646 1.86865365 2.9009471 5.1028255
  4.75282718 \ -2.37740208 \ -2.74905513 \ -3.94539386 \ -2.45767779 \ \ 4.49870622
 -4.74962366 4.55818668 4.65647563 -0.59536061 -4.19274504 1.24511478
 -3.8973661 -1.04011885 -0.26481368 -2.28654173 2.16800687 4.92252054
  2.94043056 0.5333243 4.79756441 0.43627901 -0.86060974 3.35301358
 -1.41157203 0.06996948 2.14622611 1.8217317
                                               4.29591723 2.45076112
 -0.63614187 -1.91125437 4.94259785 2.30714669 -2.39602395 4.63460325
 -3.05933115 -2.51371899 -4.71726272 2.55024272 3.42703614 4.7868769
  4.21201842 -3.5424867 -4.50429917 -0.48099319 0.1316062
                                                           4.24485554
  3.99975326 4.84343426 -2.07181554 3.98489739 1.19557716 -1.65011212
  2.41928082 - 4.7743059 - 2.80624142 2.12898243 4.66082827 - 3.45711962
  -2.45991397 0.12189604 2.88425693 -1.36533547 -1.58816079 -4.39826434
 -4.8054921 0.56007872 -3.78564008 2.50915003 3.3040424311
('Tolerance=', 27512897.560719263)
('error=', 41.810947541672022)
In [5]: import sympy
       from pandas import DataFrame
       from sympy import *
       # For Final report we need to put 'Time elapsed', 'Iteration','Tolerance',
       ### Fill value instead of 1 2 3 .....
       t = [[215.57,99999,11.96,0.05617], #Gradient method (Armijo Rule)
```

[14.09,99999,16.64,0.08595], #Gradient method

[192.15 ,99999 ,4972171.18 ,99.15], #Newton method

[77.44 ,99999 ,27512897.56 ,41.81]] #Quasi Newton method

[293.55 ,99999 ,4972171.18 ,4.24e-12], #Newton method (Armijo Rule)

[0.0035 ,2 ,2.99e-6 ,6.43e-13], #Quasi Newton method (Armijo Rule)

```
table = DataFrame(t, index=['Gradient method (Armijo Rule)', 'Gradient method
                          columns=['Time elapsed', 'Iteration', 'Tolerance', 'Error
        table
Out [5]:
                                           Time elapsed Iteration
                                                                        Tolerance
        Gradient method (Armijo Rule)
                                               215.5700
                                                              99999 1.196000e+01
        Gradient method
                                                14.0900
                                                              99999 1.664000e+01
                                               293.5500
        Newton method (Armijo Rule)
                                                              99999 4.972171e+06
        Newton method
                                               192.1500
                                                              99999 4.972171e+06
        Quasi Newton method (Armijo Rule)
                                                 0.0035
                                                                 2 2.990000e-06
        Ouasi Newton method
                                                77.4400
                                                              99999 2.751290e+07
                                                  Error
        Gradient method (Armijo Rule)
                                           5.617000e-02
        Gradient method
                                           8.595000e-02
        Newton method (Armijo Rule)
                                           4.240000e-12
        Newton method
                                           9.915000e+01
        Quasi Newton method (Armijo Rule) 6.430000e-13
        Quasi Newton method
                                           4.181000e+01
```

1.8 E)

Estimate the value of the regression coefficients y implementing the coordinate gradient method and the stochastic gradient method. Compare their performance with the algorithms in c).

```
In [88]: #definition of partial gradient

def least_sq_reg_der_par(beta_ls,X,Y,i):
    beta_ls=np.matrix(beta_ls)
    pp=-2*(Y[i]-X[i,]*np.transpose(beta_ls))*X[i,]
    aa= np.squeeze(np.asarray(pp))
    return aa
```

1.8.1 Coordinate gradient

```
In [89]: import time
    import random

    (a,b)=X.shape
    #alpha= 0.0000001
    beta_coor=np.zeros(b) #initial value for beta
    n_iter=100000 #maximim number iteration
    OF_iter=np.zeros(n_iter)
    tol_iter=np.zeros(n_iter)
    alpha_iter=np.zeros(n_iter)
    i=0;
    tol=1000;
    epsilon=1e-3;
```

```
time_start = time.clock()
        while (i <= n_iter-2) and (tol>epsilon):
            i=i+1
            grad = least_sq_reg_der(beta_coor, X, Y)
            ddirect =np.zeros(b)
            j = random.randint(0, b-1)
            ddirect[j] = - qrad[j]
             Armijo Rule----Choose an appropiate alpha
            sigma = 0.1
            beta = 0.5
            alpha = 1
            alpha = alpha*beta
            beta_coor = beta_coor + alpha*ddirect
            OF_iter[i] = least_sq_reg(beta_coor, X, Y)
            tol = np.linalg.norm(grad, ord=2)
            tol_iter[i] = tol
            alpha_iter[i] = alpha
        time elapsed = (time.clock() - time start)
        print('time elapsed=',time_elapsed)
        print('iterations',i)
        print (OF_iter[i])
        print (beta_coor)
        print (np.transpose (beta_ls_exact) )
        print('Tolerance=',tol)
        print('error=', np.linalg.norm(np.transpose(beta_ls_exact)-beta_coor, ord=2)
('time elapsed=', 163.64487752970308)
('iterations', 99999)
84919.7410451
[-2.50021396 \quad 2.18682373 \quad -3.33330932 \quad 2.39975782 \quad -2.92014081 \quad 2.00246299
 -2.92190745 \quad 0.38682466 \quad 1.41610014 \quad 3.80388697 \quad -3.04994025 \quad -0.58761597
 4.12933115 3.27038748 4.05991182 1.86812078 2.90038461 5.10213145
  4.7520726 \quad -2.37795869 \quad -2.74969627 \quad -3.94575757 \quad -2.45870403 \quad 4.49820917
-4.75009063 4.55768429 4.65587883 -0.59582511 -4.19314339 1.24460461
-3.89808893 -1.04057926 -0.26554226 -2.28768565 2.16739383 4.92170907
 2.93963913 0.53277756 4.79699291 0.43585696 -0.86131784 3.3522031
-1.41222325 0.06931246 2.14531845 1.82115116 4.29541405 2.45009805
 -0.63666568 -1.91204923 4.94201387 2.30657644 -2.39688656 4.63435576
-3.05973144 -2.51412631 -4.71816209 2.54908238 3.42649047 4.78616836
  4.2115354 \quad -3.54344122 \quad -4.50507367 \quad -0.48169823 \quad 0.13078017 \quad 4.24435255
  4.7720993 1.38526205 -4.99358747 0.74918188 3.95849775 2.79061004
 3.99931219 4.84301543 -2.07213891 3.98423849 1.19489186 -1.65072046
 2.41891899 - 4.77456556 - 2.80681004 \ 2.1282199 \ 4.66004788 - 3.45777118
  3.31367115 - 4.59191388 - 0.09910009   4.70386052 - 4.95080481   2.87758379
```

```
-2.46041758 0.12123455 2.88339249 -1.36639218 -1.58913823 -4.39890042
-4.80587062 0.55896863 -3.78642918 2.50807425 3.303280321
[-2.82009166 \quad 2.18757262 \quad -3.33272408 \quad 2.40050035 \quad -2.91964431 \quad 2.00327309
 -2.92131935 0.38737545 1.41670728 3.80403217 -3.04939149 -0.58693972
  4.13024247 3.27121943 4.06064646 1.86865365 2.9009471 5.1028255
  4.75282718 -2.37740208 -2.74905513 -3.94539386 -2.45767779 4.49870622
 -4.74962366 4.55818668 4.65647563 -0.59536061 -4.19274504 1.24511478
 -3.8973661 -1.04011885 -0.26481368 -2.28654173 2.16800687 4.92252054
  2.94043056 0.5333243 4.79756441 0.43627901 -0.86060974 3.35301358
 -1.41157203 0.06996948 2.14622611 1.8217317
                                               4.29591723 2.45076112
 -0.63614187 \ -1.91125437 \ \ 4.94259785 \ \ 2.30714669 \ -2.39602395 \ \ 4.63460325
 -3.05933115 -2.51371899 -4.71726272 2.55024272 3.42703614 4.7868769
  4.21201842 -3.5424867 -4.50429917 -0.48099319 0.1316062
                                                           4.24485554
  3.99975326 4.84343426 -2.07181554 3.98489739 1.19557716 -1.65011212
  2.41928082 - 4.7743059 - 2.80624142 2.12898243 4.66082827 - 3.45711962
  3.31431908 - 4.59174474 - 0.0981666 4.70477382 - 4.95014286 2.87792284
 -2.45991397 0.12189604 2.88425693 -1.36533547 -1.58816079 -4.39826434
 -4.8054921 0.56007872 -3.78564008 2.50915003 3.30404243]]
('Tolerance=', 4.4303189821277034)
('error=', 0.0098751677873833519)
```

1.9 Stochastic gradient

```
In [90]: (a,b) = X.shape
        #alpha= 0.0000001
        beta sto=np.zeros(b) #initial value for beta
        n_iter=100000 #maximum number iteration
        OF_iter=np.zeros(n_iter)
        tol_iter=np.zeros(n_iter)
        alpha_iter=np.zeros(n_iter)
        i=0;
        tol=1000;
        epsilon=1e-3;
        time start = time.clock()
        while (i <= n iter-2) and (tol>epsilon):
            i=i+1
            j = random.randint(0, b-1)
            grad_par = least_sq_reg_der_par(beta_sto, X, Y, j)
            grad = least_sq_reg_der(beta_sto, X, Y)
            ddirect = - grad par
            Armijo Rule----Choose an appropiate alpha
            sigma = 0.1
            beta = 0.5
            alpha = 1
```

```
alpha = alpha*beta
            beta_sto = beta_sto + ddirect*alpha
            OF_iter[i] = least_sq_reg(beta_sto, X, Y)
            tol = np.linalg.norm(grad, ord=2)
            tol iter[i] = tol
            alpha_iter[i] = alpha
        time_elapsed = (time.clock() - time_start)
        print('time elapsed=',time_elapsed)
        print('iterations',i)
        print (OF_iter[i])
        print (beta_sto)
        print (np.transpose (beta_ls_exact))
        print('Tolerance=',tol)
        print('error=', np.linalg.norm(np.transpose(beta_ls_exact)-beta_sto, ord=2)/
('time elapsed=', 322.0782561465603)
('iterations', 99999)
2113446.74323
[ \ 0.10969587 \ \ 2.15459106 \ -2.73794796 \ \ \ 2.43062366 \ -1.81939819 \ \ 1.55858974
-2.06132185 1.17113482 0.49903371 1.57226603 -0.64545193 -0.10494674
 5.42318687 1.38397385 2.23523869 2.42252443 2.59244987 3.03017531
 4.35250852 - 0.45845149 - 2.30684351 - 3.81494188 - 1.9625614 2.64530825
-2.50652389 4.22243716 3.39618464 1.15481196 -3.14793245 2.51914073
-1.94143724 -0.90108007 -0.03820853 -1.42390156 2.09482173 1.95039804
-1.77012151 1.55584506 2.69934517 1.4177997 -1.7876631
                                                        1.38743046
-0.57572693 \quad 2.07897314 \quad 0.04608848 \quad 0.83539717 \quad 4.01770176 \quad 1.29246787
-0.06485886 -1.26403007 3.41106878 1.65507843 -1.80252834 3.02580618
-1.95996077 -0.67287535 -3.8303346 1.53249861 2.95217127 3.50176353
 3.30527248 - 1.89845257 - 1.97434118 0.15292702 - 1.0444904 2.73142989
 2.0422938 1.27693678 -3.35879968 1.12025885 2.81241255 0.76902383
 2.01769281 \quad 0.77575851 \quad 1.53522836 \quad 2.43482166 \quad -0.96953795 \quad -1.15269728
 2.71898709 -2.98207682 -1.19521613 0.38061522 2.15831357 -2.96984636
 2.2403703 - 0.82964194 1.08526317 4.11447167 - 1.7634749 0.71495591
-1.09210182 0.74986064 2.98311974 0.95349042 1.22215274 -1.3047014
-4.55340843 - 0.87160734 - 2.48210947 3.10061311 2.04836621
-2.92131935 0.38737545 1.41670728 3.80403217 -3.04939149 -0.58693972
  4.13024247 3.27121943 4.06064646 1.86865365 2.9009471
                                                         5.1028255
  -4.74962366 4.55818668 4.65647563 -0.59536061 -4.19274504 1.24511478
 -3.8973661 -1.04011885 -0.26481368 -2.28654173 2.16800687 4.92252054
  2.94043056 0.5333243 4.79756441 0.43627901 -0.86060974 3.35301358
 -1.41157203 0.06996948 2.14622611 1.8217317 4.29591723 2.45076112
 -0.63614187 \ -1.91125437 \ \ 4.94259785 \ \ 2.30714669 \ -2.39602395 \ \ 4.63460325
 -3.05933115 -2.51371899 -4.71726272 2.55024272 3.42703614 4.7868769
```

```
4.21201842 \quad -3.5424867 \quad -4.50429917 \quad -0.48099319 \quad 0.1316062 \quad 4.24485554
   4.7728776 1.38593473 -4.99300561 0.74922867 3.95908786 2.79126176
   3.99975326 4.84343426 -2.07181554 3.98489739 1.19557716 -1.65011212
  2.41928082 \ -4.7743059 \ -2.80624142 \ 2.12898243 \ 4.66082827 \ -3.45711962
  3.31431908 - 4.59174474 - 0.0981666 4.70477382 - 4.95014286 2.87792284
 -2.45991397 0.12189604 2.88425693 -1.36533547 -1.58816079 -4.39826434
 -4.8054921 0.56007872 -3.78564008 2.50915003 3.30404243]]
('Tolerance=', 259606.19719997552)
('error=', 0.74201546127562212)
In [6]: import sympy
        from pandas import DataFrame
        from sympy import *
        # For Final report we need to put 'Time elapsed', 'Iteration','Tolerance',
        ### Fill value instead of 1 2 3 .....
       t = [[163.64, 99999, 4.43, 0.0099], #Coordinate gradient
             [322.08 ,99999 ,259606.20 ,0.7420 ]] #Stochastic gradient
       table = DataFrame(t, index=['Coordinate gradient', 'Stochastic gradient'],
       table
Out[6]:
                             Time elapsed Iteration Tolerance Error
       Coordinate gradient 163.64
                                             99999
                                                           4.43 0.0099
       Stochastic gradient
                                  322.08
                                             99999 259606.20 0.7420
In [ ]:
```