- Q1) Final answer page 10-12
- O2) Final answer Page 13 -14
- Q3) Final answer Page 15 24

```
In [1]: import pandas as pd
    from pandas import DataFrame
    from sets import Set
    import numpy as np
    import random
    import matplotlib.pyplot as plt
    from numpy import linalg as LA
    import statsmodels.formula.api as smf
%matplotlib inline

#read in
    data = pd.read_csv("D3.csv", index_col=None, header=None)
```

In [2]: data

```
0
              1
                     2
                            3
0
       0.4583 0.6838 0.7048 0.6163
       0.2960 0.4277 0.4469 0.3412
1
2
       0.7317 0.8338 0.7625 1.2294
       0.7521 0.9045 0.9324 1.1811
3
       0.2971 0.4406 0.3523 0.4627
4
       0.5690 0.7744 0.7080 0.8496
5
       0.5560 0.6993 0.7811 0.8134
6
7
       0.8944 0.9993 0.8953 1.7522
       0.9532 0.9891 1.0171 1.8413
8
       0.5852 0.6853 0.7713 0.9571
9
       0.2460 0.3076 0.3997 0.4428
10
11
       0.7274 0.8168 0.8868 1.1470
       0.6883 0.8762 0.8019 1.0934
12
13
       0.0299 0.0536 0.2728 0.1728
14
       0.5465 0.6068 0.6054 0.8482
       0.3535 0.5987 0.4213 0.4845
15
       0.5786 0.7974 0.6678 0.9648
16
```

Meysam Hamel 17 0.9023 1.0985	_
18 0.0744 0.0961 (
19 0.2444 0.4324 (
20 0.8804 1.1202	1.0502 1.6452
21 0.4072 0.4359 (0.4780 0.4926
22 0.2974 0.4120 (0.4351 0.3366
23 0.9637 0.9747	1.1227 2.1088
24 0.9354 1.1511	1.0917 1.8354
25 0.7469 0.8616 (0.7649 1.2555
26 0.5351 0.5608 (0.6869 0.8578
27 0.9431 1.1252 (0.9453 2.0060
28 0.9929 1.0581	1.0494 2.2145
29 0.7302 0.8999 (0.8349 1.2542
70 0.5770 0.8100 (0.6721 0.9221
71 0.3503 0.3505 (0.5038 0.6314
72 0.2180 0.2646 (0.2760 0.4502
73 0.4936 0.5679 (0.6447 0.8384
74 0.9606 1.0949	1.1772 1.8519
75 0.0479 0.1713 (0.1343 0.1089
76 0.3572 0.3614 (0.3608 0.4457

77

78

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80

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82

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85

0.8382 1.0503 0.9573 1.6205

0.4292 0.5745 0.5343 0.7358

0.1792 0.3630 0.2189 0.3386

0.1824 0.3248 0.3863 0.3530

0.3378 0.3779 0.4452 0.3914

0.4073 0.4644 0.4095 0.5683

0.7805 1.0157 0.9044 1.3310

0.6432 0.7363 0.6515 1.1121

0.8862 0.9477 0.9715 1.6006

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```
Meysam Hamel
                          Homework 3: Linear Regression and Gradient Descent
86
      0.6251 0.7523 0.7606 0.9568
87
      0.4605 0.5385 0.6499 0.6222
      0.4725 0.7163 0.6730 0.6312
88
      0.1406 0.1990 0.2983 0.1853
89
90
      0.1904 0.2297 0.3409 0.2029
      0.9607 1.1051 0.9952 1.9249
91
92
      0.3330 0.4887 0.4263 0.4096
93
      0.2491 0.3914 0.4092 0.4393
94
      0.3888 0.6010 0.5129 0.4680
95
      0.6411 0.7634 0.7966 0.9876
      0.3298 0.4415 0.3770 0.5578
96
97
      0.7259 0.7414 0.9487 1.2807
      0.8300 0.9700 0.9045 1.6492
98
```

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100 rows × 4 columns

0.9617 1.1835 1.1587 1.8941

99

```
0 1 2 3
```

- $0\quad 0.4583\ 0.6838\ 0.7048\ 0.6163$
- 1 0.2960 0.4277 0.4469 0.3412

- 2 0.7317 0.8338 0.7625 1.2294
- 3 0.7521 0.9045 0.9324 1.1811
- 4 0.2971 0.4406 0.3523 0.4627
- 5 0.5690 0.7744 0.7080 0.8496
- 6 0.5560 0.6993 0.7811 0.8134
- 7 0.8944 0.9993 0.8953 1.7522
- 8 0.9532 0.9891 1.0171 1.8413
- 9 0.5852 0.6853 0.7713 0.9571
- 10 0.2460 0.3076 0.3997 0.4428
- 11 0.7274 0.8168 0.8868 1.1470
- 12 0.6883 0.8762 0.8019 1.0934
- 13 0.0299 0.0536 0.2728 0.1728
- 14 0.5465 0.6068 0.6054 0.8482
- 15 0.3535 0.5987 0.4213 0.4845
- 16 0.5786 0.7974 0.6678 0.9648
- 17 0.9023 1.0985 1.0148 1.8765
- 18 0.0744 0.0961 0.1261 0.2215
- 19 0.2444 0.4324 0.3031 0.3703
- 20 0.8804 1.1202 1.0502 1.6452
- 21 0.4072 0.4359 0.4780 0.4926
- 22 0.2974 0.4120 0.4351 0.3366
- 23 0.9637 0.9747 1.1227 2.1088
- 24 0.9354 1.1511 1.0917 1.8354
- 25 0.7469 0.8616 0.7649 1.2555
- 26 0.5351 0.5608 0.6869 0.8578
- 27 0.9431 1.1252 0.9453 2.0060
- 28 0.9929 1.0581 1.0494 2.2145
- 29 0.7302 0.8999 0.8349 1.2542
-
- 70 0.5770 0.8100 0.6721 0.9221
- 71 0.3503 0.3505 0.5038 0.6314

- $72 \ 0.2180 \ 0.2646 \ 0.2760 \ 0.4502$
- 73 0.4936 0.5679 0.6447 0.8384
- 74 0.9606 1.0949 1.1772 1.8519
- 75 0.0479 0.1713 0.1343 0.1089
- 76 0.3572 0.3614 0.3608 0.4457
- 77 0.8382 1.0503 0.9573 1.6205
- 78 0.4292 0.5745 0.5343 0.7358
- 79 0.1792 0.3630 0.2189 0.3386
- 80 0.1824 0.3248 0.3863 0.3530
- 81 0.3378 0.3779 0.4452 0.3914
- 82 0.4073 0.4644 0.4095 0.5683
- 83 0.7805 1.0157 0.9044 1.3310
- 84 0.6432 0.7363 0.6515 1.1121
- 85 0.8862 0.9477 0.9715 1.6006
- 86 0.6251 0.7523 0.7606 0.9568
- 87 0.4605 0.5385 0.6499 0.6222
- 88 0.4725 0.7163 0.6730 0.6312
- 89 0.1406 0.1990 0.2983 0.1853
- 90 0.1904 0.2297 0.3409 0.2029
- 91 0.9607 1.1051 0.9952 1.9249
- 92 0.3330 0.4887 0.4263 0.4096
- 93 0.2491 0.3914 0.4092 0.4393
- 94 0.3888 0.6010 0.5129 0.4680
- 95 0.6411 0.7634 0.7966 0.9876
- 96 0.3298 0.4415 0.3770 0.5578
- 97 0.7259 0.7414 0.9487 1.2807
- 98 0.8300 0.9700 0.9045 1.6492
- 99 0.9617 1.1835 1.1587 1.8941

$100 \text{ rows} \times 4 \text{ columns}$

```
In [5]:
               test
               #Test Data
          1
                 2
                        3
   0
99 0.9617 1.1835 1.1587 1.8941
68 0.9968 1.1830 1.1533 2.0711
38 0.2851 0.5135 0.4872 0.4692
39 0.6396 0.6811 0.6868 0.9443
11 0.7274 0.8168 0.8868 1.1470
77 0.8382 1.0503 0.9573 1.6205
46 0.6331 0.8574 0.6413 0.9542
16 0.5786 0.7974 0.6678 0.9648
81 0.3378 0.3779 0.4452 0.3914
30 0.6795 0.8793 0.6882 1.1521
```

```
In [6]: tdata #Training Data
```

1 2 3 0.4583 0.6838 0.7048 0.6163 1 0.2960 0.4277 0.4469 0.3412 0.7317 0.8338 0.7625 1.2294 0.7521 0.9045 0.9324 1.1811 0.2971 0.4406 0.3523 0.4627 0.5690 0.7744 0.7080 0.8496 5 0.5560 0.6993 0.7811 0.8134 0.8944 0.9993 0.8953 1.7522 7 0.9532 0.9891 1.0171 1.8413 0.5852 0.6853 0.7713 0.9571 10 0.2460 0.3076 0.3997 0.4428

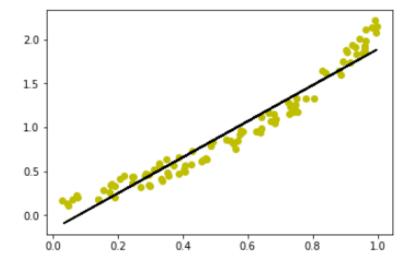
- 12 0.6883 0.8762 0.8019 1.0934
- 13 0.0299 0.0536 0.2728 0.1728
- 14 0.5465 0.6068 0.6054 0.8482
- 15 0.3535 0.5987 0.4213 0.4845
- 17 0.9023 1.0985 1.0148 1.8765
- 18 0.0744 0.0961 0.1261 0.2215
- 19 0.2444 0.4324 0.3031 0.3703
- 20 0.8804 1.1202 1.0502 1.6452
- 21 0.4072 0.4359 0.4780 0.4926
- 22 0.2974 0.4120 0.4351 0.3366
- 23 0.9637 0.9747 1.1227 2.1088
- 24 0.9354 1.1511 1.0917 1.8354
- 25 0.7469 0.8616 0.7649 1.2555
- 26 0.5351 0.5608 0.6869 0.8578
- 27 0.9431 1.1252 0.9453 2.0060
- 28 0.9929 1.0581 1.0494 2.2145
- 29 0.7302 0.8999 0.8349 1.2542
- 31 0.3889 0.5070 0.6155 0.6616
- 32 0.2702 0.5009 0.3327 0.3264
-
- 66 0.5621 0.7441 0.6466 0.7546
- 67 0.9143 1.1580 1.0035 1.7364
- 69 0.3725 0.6067 0.6148 0.5720
- $70 \ 0.5770 \ 0.8100 \ 0.6721 \ 0.9221$
- 71 0.3503 0.3505 0.5038 0.6314
- 72 0.2180 0.2646 0.2760 0.4502
- 73 0.4936 0.5679 0.6447 0.8384
- 74 0.9606 1.0949 1.1772 1.8519
- 75 0.0479 0.1713 0.1343 0.1089
- 76 0.3572 0.3614 0.3608 0.4457
- 78 0.4292 0.5745 0.5343 0.7358

•	m Hame 0.1792			Homework 3: Linear Regression and Gradient Descent 0.3386
80	0.1824	0.3248	0.3863	0.3530
82	0.4073	0.4644	0.4095	0.5683
83	0.7805	1.0157	0.9044	1.3310
84	0.6432	0.7363	0.6515	1.1121
85	0.8862	0.9477	0.9715	1.6006
86	0.6251	0.7523	0.7606	0.9568
87	0.4605	0.5385	0.6499	0.6222
88	0.4725	0.7163	0.6730	0.6312
89	0.1406	0.1990	0.2983	0.1853
90	0.1904	0.2297	0.3409	0.2029
91	0.9607	1.1051	0.9952	1.9249
92	0.3330	0.4887	0.4263	0.4096
93	0.2491	0.3914	0.4092	0.4393
94	0.3888	0.6010	0.5129	0.4680
95	0.6411	0.7634	0.7966	0.9876
96	0.3298	0.4415	0.3770	0.5578
97	0.7259	0.7414	0.9487	1.2807
98	0.8300	0.9700	0.9045	1.6492

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90 rows × 4 columns

```
In [7]: #linear regression scatter
    fit = np.polyfit(data[0], data[3], 1)
    fit_fn = np.poly1d(fit)
    plt.plot(data[0], data[3], 'yo', data[0], fit_fn(data[0]), '--k')
```



Problem 1 A)

Y = 2.048 x - 0.1612

X	Y
0.3	1.88713478225
0.5	3.93542391976
0.8	5.98371305727

Problem 1 Part b)

I randomly selected 10 points for test data and left the other 90 for training data. After calculating using regression on the training data, I was left with M = 2.039x - 0.1512 and I found the generalization error of 0.0192996468815

Problem 1 C)

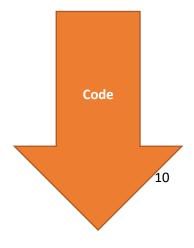
Model	0.3	0.5	0.8
$1.655 x^2 + 0.2487 x + 0.1958$	2.0993594371	7.31257151504	15.8354446974
$0.1758 \times ^{4}+1.077 \times ^{3}-0.3761 \times ^{2}+1.177 \times +0.09765$	2.15127918332	12.3749967934	43.5580092174
$-0.9501 \text{ x}^5 + 2.631 \text{ x}^4 - 1.209 \text{ x}^3 + 0.5445 \text{ x}^2 + 1.028 \text{ x} + 0.104$	2.14860875989	6.35831777391	-42.3161845583

Problem 1 D)

For the cross validation I used the same test and training data from 1b. However, this time I calculated the models using the polynomial regressions. The generalization error was then calculated using these models.

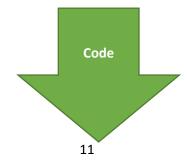
Polynomial	Model	Error
2	$1.651 x^2 + 0.2603 x + 0.1934$	0.00489796576083
3	$1.607 \text{ x}^3 - 0.8535 \text{ x}^2 + 1.324 \text{ x} + 0.08702$	0.00568684383895
4	$0.9041 \text{ x}^4 - 0.2457 \text{ x}^3 + 0.3792 \text{ x}^2 + 1.032 \text{ x} + 0.1044$	0.00593551475353
5	$1.484 \text{ x}^5 - 2.895 \text{ x}^4 + 3.253 \text{ x}^3 - 1.01 \text{ x}^2 + 1.253 \text{ x} + 0.09508$	0.00603435414003

<u>Problem 1 Part a and c</u>



```
In [8]: #Problem 1a+1c
         #polynomial regression 1-5
         for i in range(1,6):
             fit = np.polyfit(data[0],data[3],i)
             fit fn = np.poly1d(fit)
             print "polynomial: ",i
             print fit fn
             print "0.3: ", fit fn(1)
             print "0.5: ", fit_fn(2)
             print "0.8: ", fit_fn(3)
        polynomial: 1
         2.048 x - 0.1612
         0.3: 1.88713478225
         0.5: 3.93542391976
         0.8: 5.98371305727
        polynomial: 2
         1.655 \times + 0.2487 \times + 0.1958
         0.3: 2.0993594371
         0.5: 7.31257151504
         0.8: 15.8354446974
        polynomial: 3
               3
         1.439 \times - 0.6187 \times + 1.235 \times + 0.09416
         0.3: 2.14957133621
         0.5: 11.60261107
         0.8: 37.0882251144
        polynomial: 4
                           3
         0.1758 \times + 1.077 \times - 0.3761 \times + 1.177 \times + 0.09765
         0.3: 2.15127918332
         0.5: 12.3749967934
         0.8: 43.5580092174
        polynomial: 5
         -0.9501 \times + 2.631 \times - 1.209 \times + 0.5445 \times + 1.028 \times + 0.104
        0.3: 2.14860875989
        0.5: 6.35831777391
         0.8: -42.3161845583
```

Problem 1 Part b and d



Part b)

```
In [9]: #Problem 1b+1d
         #polynomial regression 1-5 on Training Data and Test Data
         for i in range(1,6):
            fit = np.polyfit(tdata[0],tdata[3],i)
            fit fn = np.poly1d(fit)
            print "polynomial: ",i
            print fit fn
             print ""
            \mathbf{M} = 0;
             for row in test.iterrows():
                x = fit fn(row[1][0]) - row[1][3]
                 M += x * x
             print "(M(x)-y)^2: ", M/sel
             print ""
         polynomial: 1
         2.039 \times - 0.1512
         (M(x)-y)^2: 0.0192966468815
         polynomial: 2
                2
         1.651 \times + 0.2603 \times + 0.1934
         (M(x)-y)^2: 0.00489796576083
         polynomial: 3
         1.607 \times -0.8535 \times +1.324 \times +0.08702
         (M(x)-y)^2: 0.00568684383895
         polynomial: 4
                             3
         0.9041 \times -0.2457 \times +0.3792 \times +1.032 \times +0.1044
         (M(x)-y)^2: 0.00593551475353
         polynomial: 5
                               3
         1.484 \times - 2.895 \times + 3.253 \times - 1.01 \times + 1.253 \times + 0.09508
         (M(x)-y)^2: 0.00603435414003
```

Problem 2 Part a)

$$Y = 2.2850x_1 - 0.2913x_2 + 0.0667x_3 - 0.1360$$

(x ₁ , x ₂ , x ₃)	y
(0.3,0.4,0.1)	0.439632732168
(0.5,0.2,0.4)	0.974889919898
(0.8,0.2,0.7)	1.68039532756

Problem 2 Part b)

For the cross validation I used the same test and training data from part 1. However this time I used all the variables from the training data to acquire the linear regression model. The generalization error was then calculated using all of the variables from the testing data.

 $Y = 2.529848 \; x_1 \; \text{--} \; 0.411109 \; x_2 \; \text{--} 0.068430 \; x_3 \; \text{--} 0.094904$

 $(M(x)-y)^2$: 0.0241688387617

```
In [10]: #basic multivariable regression
    lm = smf.ols(formula='data[3] ~ data[0] + data[1] + data[2]', data = data).fit()
    lm.summary()
```

Out[10]:

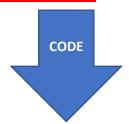
OLS Regression Results

Dep. Variable:	data[3]	R-squared:	0.945
Model:	OLS	Adj. R-squared:	0.943
Method:	Least Squares	F-statistic:	547.8
Date:	Sun, 29 Oct 2017	Prob (F-statistic):	3.12e-60
Time:	20:07:55	Log-Likelihood:	54.682
No. Observations:	100	AIC:	-101.4
Df Residuals:	96	BIC:	-90.94
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.1360	0.046	-2.935	0.004	-0.228	-0.044
data[0]	2.2850	0.297	7.702	0.000	1.696	2.874
data[1]	-0.2913	0.200	-1.454	0.149	-0.689	0.106
data[2]	0.0667	0.212	0.314	0.754	-0.355	0.488

Omnibus:	19.445	Durbin-Watson:	1.869
Prob(Omnibus):	0.000	Jarque-Bera (JB):	5.991
Skew:	0.281	Prob(JB):	0.0500
Kurtosis:	1.940	Cond. No.	38.4

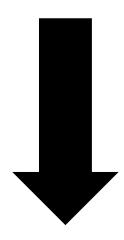
<u>Problem 2 Part a and b</u>



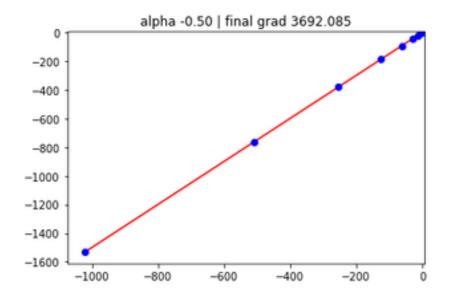
```
In [11]: #Least squares helper function uses current lm params
         def leastSquares(x1, x2, x3):
            return lm.params[0] + lm.params[1] * x1 + lm.params[2] * x2 + lm.params[3] * x3
In [12]: #Problem 2a
         print leastSquares(0.3,0.4,0.1)
         print leastSquares(0.5,0.2,0.4)
         print leastSquares(0.8,0.2,0.7)
         0.439632732168
         0.974889919898
         1.68039532756
In [13]: #Problem 2b
         lm = smf.ols(formula='tdata[3] ~ tdata[0] + tdata[1] + tdata[2]', data = tdata).fit()
         M = 0.0;
         print "parameters:"
         print lm.params
         print ""
         for row in test.iterrows():
             x = leastSquares(row[1][0], row[1][1], row[1][2]) - row[1][3]
             x^*x =+ M
         print "(M(x)-y)^2: ", M/sel
         parameters:
         Intercept -0.094904
         tdata[0]
                     2.529848
                    -0.411109
         tdata[1]
                    -0.068430
         tdata[2]
         dtype: float64
         (M(x)-y)^2: 0.0241688387617
```

Problem 3 Function1:

$$F1(x,y) = (x-5)^2 + (y+2)^2$$

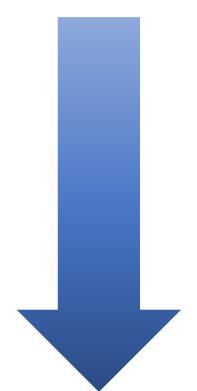


```
In [14]: #Problem 3
         #Function 1
         def func(x,y):
            return (x-5) **2 + (y+2) **2
         def func_grad(vx,vy):
           dfdx = 2.0*vx - 4.0
            dfdy = 2.0*vy - 6.0
            return np.array([dfdx,dfdy])
         #prepare for contour plot
         xlist = np.linspace(0, 5, 26)
         ylist = np.linspace(0, 5, 26)
         x, y = np.meshgrid(xlist, ylist)
         z = func(x, y)
         lev = np.linspace(0,20,21)
         #iterate location
         v init = np.array([0,0])
         num iter = 10
         values = np.zeros([num_iter,2])
         for alpha in [.5,-.5]:
            values[0,:] = v_init
            v = v init
            print "iter: ", 1, "value: ", v, "func: ", func(v[0],v[1])
             # actual gradient descent algorithm
             for i in range(1, num iter):
                v = v - alpha * func_grad(v[0],v[1])
                values[i,:] = v
                print "iter: ", i+1, "v: ", v, "func: ", func(v[0],v[1])
             #plotting
             plt.contour(x,y,z,levels=lev)
             plt.plot(values[:,0],values[:,1],'r-')
            plt.plot(values[:,0],values[:,1],'bo')
             grad norm = LA.norm(func grad(v[0],v[1]))
             title = "alpha %0.2f | final grad %0.3f" % (alpha, grad norm)
            plt.title(title)
        iter: 1 value: [0 0] func: 29
         iter: 2 v: [ 2. 3.] func: 34.0
         iter: 3 v: [ 2. 3.] func: 34.0
        iter: 4 v: [ 2. 3.] func: 34.0
         iter: 5 v: [ 2. 3.] func: 34.0
         iter: 6 v: [ 2. 3.] func: 34.0
         iter: 7 v: [ 2. 3.] func: 34.0
         iter: 8 v: [ 2. 3.] func: 34.0
        iter: 9 v: [ 2. 3.] func: 34.0
        iter: 10 v: [ 2. 3.] func: 34.0
        iter: 1 value: [0 0] func: 29
        iter: 2 v: [-2. -3.] func: 50.0
        iter: 3 v: [-6. -9.] func: 170.0
        iter: 4 v: [-14. -21.] func: 722.0
        iter: 5 v: [-30. -45.] func: 3074.0
        iter: 6 v: [-62. -93.] func: 12770.0
        iter: 7 v: [-126. -189.] func: 52130.0
        iter: 8 v: [-254. -381.] func: 210722.0
        iter: 9 v: [-510. -765.] func: 847394.0
        iter: 10 v: [-1022. -1533.] func: 3398690.0
```



Problem 3 Function2:

$$F2(x,y) = (1-(y-4))2+35((x+6)-(y-4)2)2$$



```
In [17]: #Problem 3
         #Function 1
         def func(x,y):
             return (1-(y-4))**2 + 35*((x+6)-(y-4)**2)**2
         def func grad(vx,vy):
            dfdx = 40*vx - 40*(vy - 3)**2 + 120
             dfdy = 2*vy + 20*(-4*vy + 12)*(vx - (vy - 3)**2 + 3) - 8
             return np.array([dfdx,dfdy])
         #prepare for contour plot
         xlist = np.linspace(0, 5, 26)
         ylist = np.linspace(0, 5, 26)
         x, y = np.meshgrid(xlist, ylist)
         z = func(x, y)
         lev = np.linspace(0,20,21)
          init = np.array([0,0])
         num iter = 100
         values = np.zeros([num iter,2])
         for alpha in [1.0/8592,1.0/481.69,.5]:
            print alpha
             values[0,:] = v_init
             v = v init
            print "iter: ", 1, "value: ", v, "func: ", func(v[0],v[1])
             # actual gradient descent algorithm
             for i in range(1, num iter):
                 v = v - alpha * func_grad(v[0],v[1])
                 values[i,:] = v
                 print "iter: ", i+1, "v: ", v, "func: ", func(v[0],v[1])
             #plotting
            plt.contour(x,y,z,levels=lev)
            plt.plot(values[:,0], values[:,1], 'r-')
            plt.plot(values[:,0],values[:,1],'bo')
            grad_norm = LA.norm(func_grad(v[0],v[1]))
             title = "alpha %0.2f | final grad %0.3f" % (alpha,grad_norm)
             plt.title(title)
             file = "gd-%2.0f.pdf" % (alpha*100)
             plt.savefig(file, bbox inches='tight')
             plt.clf()
             plt.cla()
```

0.000116387337058

```
iter: 1 value: [0 0] func: 3525
iter: 2 v: [ 0.02793296    0.16852886] func: 2643.48596102
iter: 3 v: [ 0.0511606    0.30095749] func: 2060.60991683
iter: 4 v: [ 0.07087042    0.40821383] func: 1653.82348808
iter: 5 v: [ 0.08784661    0.4970472 ] func: 1358.23585821
iter: 6 v: [ 0.10263676    0.57190074] func: 1136.59017022
iter: 7 v: [ 0.11563969    0.63584352] func: 966.140909989
iter: 8 v: [ 0.1271555    0.69107697] func: 832.313692687
iter: 9 v: [ 0.13741607    0.73922893] func: 725.39672674
iter: 10 v: [ 0.14660448    0.78153372] func: 638.705121322
iter: 11 v: [ 0.15486793    0.81894725] func: 567.510017194
iter: 12 v: [ 0.1623266    0.85222324] func: 508.387195633
iter: 13 v: [ 0.16907994    0.88196532] func: 458.806532969
iter: 14 v: [ 0.17521119    0.90866349] func: 416.865231055
```

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iter:	15 v:	[0.93272031]	func:	381.10980871
iter:	16 v:	[0.95447001]	func:	350.414519043
iter:	17 v:	[0.19052611	0.97419273]	func:	323.896573888
iter:	18 v:	[0.1947783	0.99212527]	func:	300.855933585
iter:	19 v:	[0.19867393	1.00846933]	func:	280.731830614
iter:	20 v:	[0.20224712	1.0233979]	func:	263.070903959
iter:	21 v:	[0.20552789	1.03706032]	func:	247.503524715
iter:	22 v:	[0.2085428	1.04958622]	func:	233.7259886
iter:	23 v:	ſ	0.21131548	1.06108874]	func:	221.486969051
iter:	24 v:	Ī	0.21386698	1.07166709	func:	210.577103802
iter:	25 v:	ſ	0.21621614	1.08140868]	func:	200.820913042
iter:	26 v:	ſ	0.21837991	1.09039081]	func:	192.070471208
iter:	27 v:	[0.22037352	1.09868213]	func:	184.200410979
iter:		-	0.22221074	1.10634378]	func:	177.103948692
		[-		
iter:	29 v:	[0.22390405	1.11343045]	func:	170.689699695
iter:	30 v:	[0.22546476	1.11999115]	func:	164.879109556
iter:	31 v:	[0.22690317	1.12606995]	func:	159.604369013
iter:	32 v:	[0.22822863	1.1317066]	func:	154.806711616
iter:	33 v:	[0.22944973	1.136937]	func:	150.435016099
iter:	34 v:	[0.23057428	1.14179368]	func:	146.444652948
iter:	35 v:	[0.23160946	1.14630615]	func:	142.796527786
iter:	36 v:	Ī	0.23256184	1.15050126]	func:	139.456284297
iter:	37 v:	Ī	0.23343747	1.15440348]	func:	136.393637124
iter:	38 v:	Ĺ	0.23424188	1.15803512]	func:	133.581811209
iter:	39 v:	[0.23498021	1.16141661]	func:	130.997068694
iter:	40 v:	-	0.23565716	1.16456661]	func:	128.618308185
_		[_		
iter:	41 v:	[0.23627708	1.16750227]	func:	126.426724079
iter:	42 v:	[0.23684398	1.1702393]	func:	124.405515928
iter:	43 v:	[0.23736158	1.17279216]	func:	122.539639673
iter:	44 v:	[0.23783331	1.17517415]	func:	120.815594027
iter:	45 v:	[0.23826234	1.17739752]	func:	119.221236472
iter:	46 v:	[0.23865162	1.17947355]	func:	117.745624304
iter:	47 v:	[0.23900388	1.18141269]	func:	116.378876903
iter:	48 v:	[0.23932164	1.18322455]	func:	115.112056089
iter:	49 v:	[0.23960727	1.18491804]	func:	113.937061887
iter:	50 v:	[0.23986292	1.1865014]	func:	112.846541499
iter:	51 v:	Ī	0.24009064	1.18798225]	func:	111.833809596
iter:	52 v:	Ī	0.24029231	1.18936766]	func:	110.892778366
iter:	53 v:	ſ	0.24046967	1.19066418]	func:	110.017895966
iter:	54 v:	[0.24062435	1.19187788]	func:	109.20409225
iter:	55 v:	[0.24075788	1.1930144	func:	108.44673081
iter:	56 v:	[0.24087166	1.19407897]	func:	107.741566492
		-		_		
iter:	57 v:	[0.240967	1.19507648]	func:	107.084707693
iter:	58 v:	[0.24104512	1.19601142]	func:	106.472582829
iter:	59 v:	[0.24110718	1.19688802]	func:	105.901910446
iter:	60 v:	[0.24115423	1.19771017]	func:	105.369672542
iter:	61 v:	[0.24118726	1.19848152]	func:	104.873090685
iter:	62 v:	[0.24120719	1.19920547]	func:	104.409604626
iter:	63 v:	[0.24121489	1.19988515]	func:	103.976853081
iter:	64 v:	[0.24121116	1.20052351]	func:	103.572656455
iter:	65 v:	[0.24119675	1.20112329]	func:	103.195001267
iter:	66 v:	ſ	0.24117235	1.20168705]	func:	102.842026106
iter:	67 v:	[0.24113863	1.20221715]	func:	102.512008926
iter:	68 v:	[0.2410962	1.20271582]	func:	102.203355547
iter:	69 v:	[0.24104561	1.20318512]	func:	101.91458923
iter:	70 v:	L	0.24104361	1.20316312]	func:	101.644341213
		-	0.24092209	_		101.844341213
iter:	71 v:	[1.20404322]	func:	
iter:	72 v:	[0.24085011	1.20443551]	func:	101.154414009

iter: 29 v: [-1.99919579 3.99993342] func: 561.225333559

```
30 v: [-1.99927363 4.00008937] func: 561.203221323
iter: 31 v: [-1.99931911 4.00017995] func: 561.190297836
iter: 32 v: [-1.99934576 4.00023252] func: 561.182722746
             [-1.99936146 4.00026298] func: 561.17825899
iter: 33 v:
             [-1.99937081 4.00028058] func: 561.175604617
iter: 34 v:
             [-1.99937645 4.0002907 ] func: 561.174002303
iter: 35 v:
iter: 36 v: [-1.99937994 4.00029648] func: 561.173011655
iter: 37 v: [-1.99938219 4.00029974] func: 561.172376628
iter: 38 v: [-1.9993837 4.00030152] func: 561.17194837
iter: 39 v: [-1.99938479 4.00030246] func: 561.171640351
             [-1.99938564 4.0003029] func: 561.171402273
[-1.99938634 4.00030305] func: 561.171204898
iter: 40 v:
iter: 41 v:
iter: 42 v:
            [-1.99938697 4.00030303] func: 561.171031231
iter: 43 v: [-1.99938754 4.00030291] func: 561.170871393
iter: 44 v: [-1.99938808 4.00030274] func: 561.170719642
iter: 45 v: [-1.99938861 4.00030254] func: 561.17057264
iter: 46 v: [-1.99938912 4.00030232] func: 561.170428447
             [-1.99938963 4.00030208] func: 561.170285935
[-1.99939014 4.00030184] func: 561.170144448
iter: 47 v:
iter: 48 v:
iter: 49 v: [-1.99939065 4.0003016 ] func: 561.170003606
iter: 50 v: [-1.99939115 4.00030136] func: 561.169863186
iter: 51 v: [-1.99939165 4.00030111] func: 561.169723061
iter: 52 v: [-1.99939215 4.00030086] func: 561.169583154
iter: 53 v: [-1.99939265 4.00030062] func: 561.169443423
             [-1.99939315 4.00030037] func: 561.169303842
[-1.99939365 4.00030012] func: 561.169164396
iter: 54 v:
iter: 55 v:
iter: 56 v: [-1.99939415 4.00029987] func: 561.169025077
iter: 57 v: [-1.99939465 4.00029963] func: 561.168885879
iter: 58 v: [-1.99939515 4.00029938] func: 561.1687468
iter: 59 v: [-1.99939565 4.00029913] func: 561.168607838
iter: 60 v: [-1.99939615 4.00029889] func: 561.168468991
             [-1.99939664 4.00029864] func: 561.16833026
[-1.99939714 4.0002984] func: 561.168191643
iter: 61 v:
iter: 62 v:
iter: 63 v: [-1.99939764 4.00029815] func: 561.168053141
iter: 64 v: [-1.99939813 4.0002979 ] func: 561.167914752
iter: 65 v:
            [-1.99939863 4.00029766] func: 561.167776478
iter: 66 v: [-1.99939912 4.00029741] func: 561.167638318
             [-1.99939962 4.00029717] func: 561.167500271
[-1.99940011 4.00029692] func: 561.167362338
[-1.99940061 4.00029668] func: 561.167224519
iter: 67 v:
iter: 68 v:
iter: 69 v:
iter: 70 v: [-1.9994011 4.00029644] func: 561.167086813
iter: 71 v: [-1.99940159 4.00029619] func: 561.16694922
iter: 72 v: [-1.99940209 4.00029595] func: 561.166811741
iter: 73 v: [-1.99940258 4.0002957 ] func: 561.166674375
             [-1.99940307 4.00029546] func: 561.166537121
iter: 74 v:
             [-1.99940356 4.00029522] func: 561.166399981
iter: 75 v:
iter: 76 v:
             [-1.99940405 4.00029497] func: 561.166262954
iter: 77 v: [-1.99940455 4.00029473] func: 561.16612604
iter: 78 v: [-1.99940504 4.00029449] func: 561.165989238
iter: 79 v:
            [-1.99940553 4.00029425] func: 561.165852549
iter: 80 v: [-1.99940602 4.000294 ] func: 561.165715972
                            4.00029376] func: 561.165579508
iter: 81 v:
             [-1.9994065
             [-1.99940699 4.00029352] func: 561.165443156
iter: 82 v:
iter: 83 v: [-1.99940748 4.00029328] func: 561.165306916
iter: 84 v: [-1.99940797 4.00029304] func: 561.165170789
iter: 85 v: [-1.99940846 4.0002928 ] func: 561.165034773
iter: 86 v: [-1.99940894 4.00029255] func: 561.16489887
iter: 87 v: [-1.99940943 4.00029231] func: 561.164763078
```

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