

Aim : Implementation of L2 regularization

```
In [1]: from sklearn.datasets import make_regression
```

```
In [2]: x, y = make_regression(n_samples=100, n_features=1, n_targets=1, noise=20, random_state=2)
```

In [3]:

x

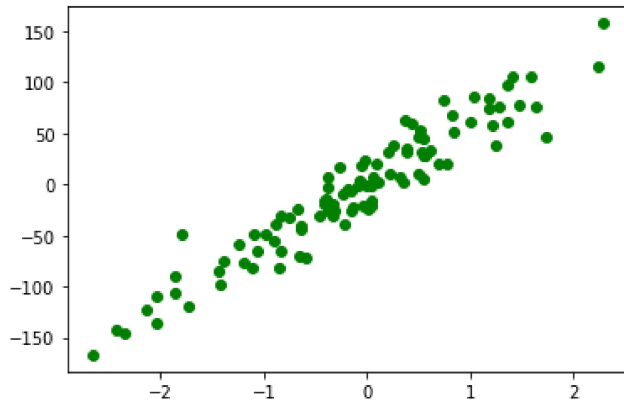
```
Out[3]: array([[ -8.78107893e-01],
 [ 1.35963386e+00],
 [ 1.64027081e+00],
 [ 5.42352572e-01],
 [ 8.24703005e-01],
 [-5.96159700e-01],
 [-5.62668272e-02],
 [-1.32328898e-01],
 [-2.43476758e+00],
 [-4.03892269e-01],
 [ 3.81866234e-01],
 [ 1.36723542e+00],
 [-7.47870949e-01],
 [-3.81516482e-01],
 [ 8.42456282e-01],
 [-7.72186654e-02],
 [ 4.33496330e-01],
 [-2.17135269e-01],
 [ 1.46767801e+00],
 [ 1.12726505e-01],
 [ 1.73118467e+00],
 [-3.35677339e-01],
 [-1.09873895e+00],
 [-8.41747366e-01],
 [ 5.66275441e-01],
 [-1.05795222e+00],
 [ 6.95119605e-01],
 [ 5.39058321e-01],
 [ 5.01857207e-01],
 [-1.43943903e+00],
 [-1.89469265e-01],
 [-7.44707629e-02],
 [-1.79343559e+00],
 [ 2.23136679e+00],
 [ 4.15393930e-02],
 [ 1.17353150e+00],
 [-1.38451867e+00],
 [ 2.16116006e-01],
 [-9.14526229e-02],
 [ 1.27837923e+00],
 [-2.13619610e+00],
 [-2.36184031e-01],
 [-1.85861239e+00],
 [ 3.26003433e-01],
 [ 9.76147160e-06],
 [-3.75669423e-01],
 [ 1.04082395e+00],
 [-3.38821966e-01],
 [-6.77675577e-01],
 [ 1.21788563e+00],
 [-1.24528809e+00],
 [-8.29135289e-01],
 [-4.19316482e-01],
 [ 3.80471970e-01],
 [-1.86809065e+00],
 [ 1.58448706e+00],
 [ 6.11340780e-01],
 [ 1.00036589e+00],
 [-9.09007615e-01],
 [-3.95702397e-02],
 [-1.91304965e-02],
 [-1.42121723e+00],
 [ 3.50888494e-01],
 [-9.88779049e-01],
 [ 4.62555231e-02],
 [-3.81092518e-01],
 [ 7.35279576e-01],
 [-6.37655012e-01],
```

```
[ -2.65944946e+00],
[ -4.16757847e-01],
[  2.56570452e-01],
[  3.70444537e-01],
[ -6.34679305e-01],
[  4.79705919e-02],
[ -2.34360319e+00],
[  5.08396243e-01],
[ -6.53250268e-01],
[ -8.44213704e-01],
[ -4.62005348e-01],
[  2.04207979e-01],
[  5.02881417e-01],
[ -2.69056960e-01],
[ -1.11792545e+00],
[  5.24296430e-01],
[  8.77102184e-02],
[  5.51454045e-01],
[ -2.03346655e+00],
[ -3.13508197e-01],
[  1.17500122e+00],
[  6.64890091e-02],
[  1.24821292e+00],
[ -1.18761229e+00],
[  1.40669624e+00],
[ -1.56434170e-01],
[  2.29220801e+00],
[ -1.73795950e+00],
[ -2.04032305e+00],
[  7.71011738e-01],
[  9.02525097e-03],
[ -1.53495196e-01]])
```

In [4]: y

```
Out[4]: array([ -39.28111368,  60.36088967,  75.52329534,  44.96973636,
  67.66126148, -72.56783539,  19.01828591, -22.48725552,
 -142.24576438, -15.18039423,  30.97837048,  96.49616637,
 -32.18524905, -2.73343352,  51.91525767,  3.15477977,
  59.67514565, -39.18356672,  77.51342439,  2.12711018,
  46.68645147, -19.761177 , -48.75839881, -64.53825927,
  28.77572075, -64.91364323,  19.42416802,  27.95857927,
  47.08740928, -84.85367831, -5.27930487,  1.63049652,
 -49.65719062, 115.44179673, -15.90690036,  84.79331953,
 -75.6361891 ,  9.44506047, -1.10256915,  75.29608508,
 -123.12209367, -9.2643982 , -89.78307298,  6.92428027,
 -1.37114106, -25.12536695,  86.08123884, -30.90683686,
 -25.0568712 ,  57.12871401, -59.45098934, -31.08914872,
 -19.63623245,  35.24070197, -105.60242742, 105.79285848,
  33.5416947 ,  61.17460846, -55.74511813, -20.22825731,
  22.61124007, -98.27810976,  2.51352804, -48.6592866 ,
 -0.80311042,  7.54015095,  82.78973256, -40.39608706,
 -167.01636233, -16.85774471,  38.07736278,  62.11552806,
 -43.76716725, -21.72322566, -145.21657026,  52.47950288,
 -70.08095861, -81.46341231, -31.22319839,  31.93634207,
  9.80885417,  16.27732067, -82.0026651 ,  32.12925769,
 19.84053667,  4.7638933 , -135.75753122, -26.07994395,
 74.9019179 ,  7.4922353 ,  37.76513716, -77.51141039,
105.71270776, -26.05475138, 157.64933729, -120.01528779,
-110.34447888,  19.41625394, -24.34594172, -6.97226993])
```

```
In [5]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
plt.scatter(x, y,c='g')
plt.show()
```



```
In [6]: from sklearn.linear_model import LinearRegression
lr = LinearRegression()
```

```
In [7]: lr.fit(x,y)
```

```
Out[7]: LinearRegression()
```

```
In [8]: lr.coef_ #Magnitude,coefficient,slope
```

```
Out[8]: array([58.11865999])
```

```
In [9]: lr.intercept_ #Bias, y_intercept
```

```
Out[9]: 0.5334392393890015
```

```
In [10]: from sklearn.model_selection import train_test_split
```

```
In [11]: x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2)
```

Ridge Regression

```
In [12]: from sklearn.linear_model import Ridge
```

```
In [13]: rr = Ridge(alpha=10)
```

```
In [14]: rr.fit(x,y)
```

```
Out[14]: Ridge(alpha=10)
```

```
In [15]: rr.coef_
```

```
Out[15]: array([53.17425635])
```

```
In [16]: rr.intercept_
```

```
Out[16]: 0.020501198988966074
```

```
In [17]: rrr = Ridge(alpha=10)
rrr.fit(x,y)
print(rrr.coef_)
print(rrr.intercept_)
```

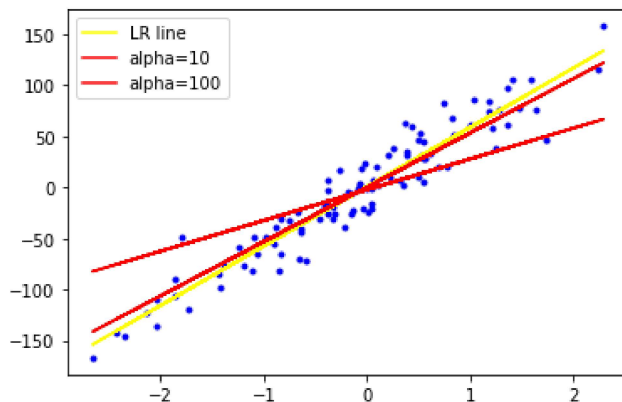
```
[53.17425635]
0.020501198988966074
```

```
In [18]: rrr = Ridge(alpha=100)
rrr.fit(x,y)
print(rrr.coef_)
print(rrr.intercept_)
```

```
[30.11564938]
-2.3716248342245936
```

```
In [19]: plt.plot(x,y, 'b.')
plt.plot(x,lr.predict(x),color='yellow',label="LR line")
plt.plot(x,rr.predict(x),color='red',label="alpha=10")
plt.plot(x,rrr.predict(x),color='red',label="alpha=100")
plt.legend()
```

Out[19]: <matplotlib.legend.Legend at 0x2973b8e9730>



Aim : Demonstrate how co-efficient affected values of the lambda(alpha)

```
In [20]: from sklearn.datasets import load_diabetes
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

```
In [21]: data = load_diabetes()
```

```
In [22]: # array to dataframe  
data
```

```

Out[22]: {'data': array([[ 0.03807591,  0.05068012,  0.06169621, ..., -0.00259226,
    0.01990842, -0.01764613],
 [-0.00188202, -0.04464164, -0.05147406, ..., -0.03949338,
    -0.06832974, -0.09220405],
 [ 0.08529891,  0.05068012,  0.04445121, ..., -0.00259226,
    0.00286377, -0.02593034],
 ...,
 [ 0.04170844,  0.05068012, -0.01590626, ..., -0.01107952,
    -0.04687948,  0.01549073],
 [-0.04547248, -0.04464164,  0.03906215, ...,  0.02655962,
    0.04452837, -0.02593034],
 [-0.04547248, -0.04464164, -0.0730303 , ..., -0.03949338,
    -0.00421986,  0.00306441]]),
 'target': array([151.,  75., 141., 206., 135.,  97., 138.,  63., 110., 310., 101.,
   69., 179., 185., 118., 171., 166., 144.,  97., 168.,  68.,  49.,
   68., 245., 184., 202., 137.,  85., 131., 283., 129.,  59., 341.,
   87.,  65., 102., 265., 276., 252.,  90., 100.,  55.,  61.,  92.,
  259.,  53., 190., 142.,  75., 142., 155., 225.,  59., 104., 182.,
  128.,  52.,  37., 170., 170.,  61., 144.,  52., 128.,  71., 163.,
  150.,  97., 160., 178.,  48., 270., 202., 111.,  85.,  42., 170.,
  200., 252., 113., 143.,  51.,  52., 210.,  65., 141.,  55., 134.,
   42., 111.,  98., 164.,  48.,  96.,  90., 162., 150., 279.,  92.,
   83., 128., 102., 302., 198.,  95.,  53., 134., 144., 232.,  81.,
  104.,  59., 246., 297., 258., 229., 275., 281., 179., 200., 200.,
  173., 180.,  84., 121., 161.,  99., 109., 115., 268., 274., 158.,
  107.,  83., 103., 272.,  85., 280., 336., 281., 118., 317., 235.,
   60., 174., 259., 178., 128.,  96., 126., 288.,  88., 292.,  71.,
  197., 186.,  25.,  84.,  96., 195.,  53., 217., 172., 131., 214.,
   59.,  70., 220., 268., 152.,  47.,  74., 295., 101., 151., 127.,
  237., 225.,  81., 151., 107.,  64., 138., 185., 265., 101., 137.,
  143., 141.,  79., 292., 178.,  91., 116.,  86., 122.,  72., 129.,
  142.,  90., 158.,  39., 196., 222., 277.,  99., 196., 202., 155.,
   77., 191.,  70.,  73.,  49.,  65., 263., 248., 296., 214., 185.,
   78.,  93., 252., 150.,  77., 208.,  77., 108., 160.,  53., 220.,
  154., 259.,  90., 246., 124.,  67.,  72., 257., 262., 275., 177.,
   71.,  47., 187., 125.,  78.,  51., 258., 215., 303., 243.,  91.,
  150., 310., 153., 346.,  63.,  89.,  50.,  39., 103., 308., 116.,
  145.,  74.,  45., 115., 264.,  87., 202., 127., 182., 241.,  66.,
   94., 283.,  64., 102., 200., 265.,  94., 230., 181., 156., 233.,
   60., 219.,  80.,  68., 332., 248.,  84., 200.,  55.,  85.,  89.,
   31., 129.,  83., 275.,  65., 198., 236., 253., 124.,  44., 172.,
  114., 142., 109., 180., 144., 163., 147.,  97., 220., 190., 109.,
  191., 122., 230., 242., 248., 249., 192., 131., 237.,  78., 135.,
  244., 199., 270., 164.,  72.,  96., 306.,  91., 214.,  95., 216.,
  263., 178., 113., 200., 139., 139.,  88., 148.,  88., 243.,  71.,
   77., 109., 272.,  60.,  54., 221.,  90., 311., 281., 182., 321.,
   58., 262., 206., 233., 242., 123., 167.,  63., 197.,  71., 168.,
  140., 217., 121., 235., 245.,  40.,  52., 104., 132.,  88.,  69.,
  219.,  72., 201., 110.,  51., 277.,  63., 118.,  69., 273., 258.,
   43., 198., 242., 232., 175.,  93., 168., 275., 293., 281.,  72.,
  140., 189., 181., 209., 136., 261., 113., 131., 174., 257.,  55.,
   84.,  42., 146., 212., 233.,  91., 111., 152., 120.,  67., 310.,
   94., 183.,  66., 173.,  72.,  49.,  64.,  48., 178., 104., 132.,
  220.,  57.]),
 'frame': None,
 'DESCR': '.. _diabetes_dataset:\n\nDiabetes dataset\n-----\n\nTen baseline variables,
age, sex, body mass index, average blood\npressure, and six blood serum measurements were obtained
for each of n =442 diabetes patients, as well as the response of interest, a\nquantitative measu
re of disease progression one year after baseline.\n\n**Data Set Characteristics:**\n\n :Number o
f Instances: 442\n\n :Number of Attributes: First 10 columns are numeric predictive values\n\n :
Target: Column 11 is a quantitative measure of disease progression one year after baseline\n\n :A
ttribute Information:\n
- age      age in years\n
- sex      \n
- bmi      body mass index\n
- bp       average blood pressure\n
- s1       tc, total serum cholesterol\n
- s2       \n
- ldl      low-density lipoproteins\n
- s3       hdl, high-density lipoproteins\n
- s4       tc\n
- h         total cholesterol / HDL\n
- s5       ltg, possibly log of serum triglycerides level\n
- s6       glu, blood sugar level\n\nNote: Each of these 10 feature variables have been mean center
ed and scaled by the standard deviation times `n_samples` (i.e. the sum of squares of each column
totals 1).\n\nSource URL:\nhttps://www4.stat.ncsu.edu/~boos/var.select/diabetes.html\n\nFor more i

```


information see:\nBradley Efron, Trevor Hastie, Iain Johnstone and Robert Tibshirani (2004) "Least Angle Regression," Annals of Statistics (with discussion), 407-499.\n(https://web.stanford.edu/~hastie/Papers/LARS/LeastAngle_2002.pdf),

```
'feature_names': ['age',
                  'sex',
                  'bmi',
                  'bp',
                  's1',
                  's2',
                  's3',
                  's4',
                  's5',
                  's6'],
'data_filename': 'diabetes_data.csv.gz',
'target_filename': 'diabetes_target.csv.gz',
'data_module': 'sklearn.datasets.data'}
```

```
In [23]: df = pd.DataFrame(data.data, columns=data.feature_names)
```

```
In [24]: df
```

Out[24]:

	age	sex	bmi	bp	s1	s2	s3	s4	s5	s6
0	0.038076	0.050680	0.061696	0.021872	-0.044223	-0.034821	-0.043401	-0.002592	0.019908	-0.017646
1	-0.001882	-0.044642	-0.051474	-0.026328	-0.008449	-0.019163	0.074412	-0.039493	-0.068330	-0.092204
2	0.085299	0.050680	0.044451	-0.005671	-0.045599	-0.034194	-0.032356	-0.002592	0.002864	-0.025930
3	-0.089063	-0.044642	-0.011595	-0.036656	0.012191	0.024991	-0.036038	0.034309	0.022692	-0.009362
4	0.005383	-0.044642	-0.036385	0.021872	0.003935	0.015596	0.008142	-0.002592	-0.031991	-0.046641
...
437	0.041708	0.050680	0.019662	0.059744	-0.005697	-0.002566	-0.028674	-0.002592	0.031193	0.007207
438	-0.005515	0.050680	-0.015906	-0.067642	0.049341	0.079165	-0.028674	0.034309	-0.018118	0.044485
439	0.041708	0.050680	-0.015906	0.017282	-0.037344	-0.013840	-0.024993	-0.011080	-0.046879	0.015491
440	-0.045472	-0.044642	0.039062	0.001215	0.016318	0.015283	-0.028674	0.026560	0.044528	-0.025930
441	-0.045472	-0.044642	-0.073030	-0.081414	0.083740	0.027809	0.173816	-0.039493	-0.004220	0.003064

442 rows × 10 columns

```
In [25]: df['Target'] = data.target
```

In [26]: df

Out[26]:

	age	sex	bmi	bp	s1	s2	s3	s4	s5	s6	Target
0	0.038076	0.050680	0.061696	0.021872	-0.044223	-0.034821	-0.043401	-0.002592	0.019908	-0.017646	151.0
1	-0.001882	-0.044642	-0.051474	-0.026328	-0.008449	-0.019163	0.074412	-0.039493	-0.068330	-0.092204	75.0
2	0.085299	0.050680	0.044451	-0.005671	-0.045599	-0.034194	-0.032356	-0.002592	0.002864	-0.025930	141.0
3	-0.089063	-0.044642	-0.011595	-0.036656	0.012191	0.024991	-0.036038	0.034309	0.022692	-0.009362	206.0
4	0.005383	-0.044642	-0.036385	0.021872	0.003935	0.015596	0.008142	-0.002592	-0.031991	-0.046641	135.0
...
437	0.041708	0.050680	0.019662	0.059744	-0.005697	-0.002566	-0.028674	-0.002592	0.031193	0.007207	178.0
438	-0.005515	0.050680	-0.015906	-0.067642	0.049341	0.079165	-0.028674	0.034309	-0.018118	0.044485	104.0
439	0.041708	0.050680	-0.015906	0.017282	-0.037344	-0.013840	-0.024993	-0.011080	-0.046879	0.015491	132.0
440	-0.045472	-0.044642	0.039062	0.001215	0.016318	0.015283	-0.028674	0.026560	0.044528	-0.025930	220.0
441	-0.045472	-0.044642	-0.073030	-0.081414	0.083740	0.027809	0.173816	-0.039493	-0.004220	0.003064	57.0

442 rows × 11 columns

In [27]: df.shape

Out[27]: (442, 11)

```
In [28]: from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(data.data,data.target,test_size=0.2,random_state=2)
```

In [29]: len(x_train)

Out[29]: 353

```
In [30]: from sklearn.linear_model import Ridge
from sklearn.metrics import r2_score
```

```
In [31]: coefs = []
r2_scores = []
for i in [0,10,100,1000]:
    reg = Ridge(alpha=i)
    reg.fit(x_train,y_train)

    coefs.append(reg.coef_.tolist())
    y_pred = reg.predict(x_test)
    r2_scores.append(r2_score(y_test,y_pred))
```

In [32]:

coefs

Out[32]:

```
[[-9.160884832463061,
 -205.46225987708985,
 516.684623831389,
 340.6273410788926,
 -895.5436086743563,
 561.2145330558951,
 153.88478595250416,
 126.73431596154839,
 861.1213995461823,
 52.41982835857488],
 [21.17400371774996,
 1.659796134738543,
 63.659771901799736,
 48.4932400316976,
 18.421491990472827,
 12.875448426495623,
 -38.9154350572375,
 38.842463722063044,
 61.61240510619145,
 35.50535526561315],
 [2.8589794382553477,
 0.6294520371235355,
 7.540604496094514,
 5.8499966438735935,
 2.7108785152669643,
 2.142134389296116,
 -4.83404696857779,
 5.108223239548698,
 7.4484662433551705,
 4.576128672131118],
 [0.2957255603009537,
 0.06929028636932703,
 0.7690038061994643,
 0.5978292887031441,
 0.2828995133533437,
 0.22593550596063292,
 -0.4956069088303586,
 0.5270313419211985,
 0.7614974792951518,
 0.4710290658232608]]
```

```

In [33]: plt.figure(figsize=(20,9))
plt.subplot(221)
plt.bar(data.feature_names,coefs[0])
plt.title("Alpha = 0,r2_score{}".format(round(r2_scores[0],2)))

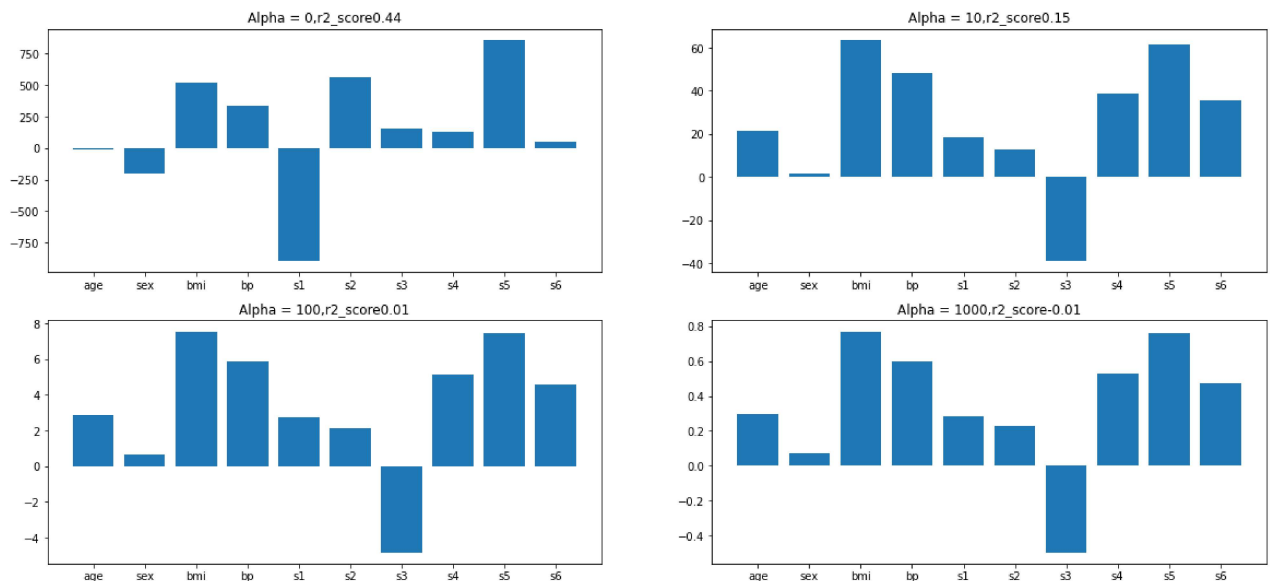
plt.subplot(222)
plt.bar(data.feature_names,coefs[1])
plt.title("Alpha = 10,r2_score{}".format(round(r2_scores[1],2)))

plt.subplot(223)
plt.bar(data.feature_names,coefs[2])
plt.title("Alpha = 100,r2_score{}".format(round(r2_scores[2],2)))

plt.subplot(224)
plt.bar(data.feature_names,coefs[3])
plt.title("Alpha = 1000,r2_score{}".format(round(r2_scores[3],2)))

```

Out[33]: Text(0.5, 1.0, 'Alpha = 1000,r2_score-0.01')



Aim : In ridge regression prove that 'The more higher co-efficient are affected more'

```

In [34]: coefs = []
alphas = [0,0.0001,0.001,0.01,0.1,1,10,100,1000,10000]
for i in alphas:
    reg = Ridge(alpha=i)
    reg.fit(x_train,y_train)
    coefs.append(reg.coef_.tolist())

```

```

In [35]: np_arr = np.array(coefs)

```

```
In [37]: coef_df = pd.DataFrame(np_arr, columns=data.feature_names)
coef_df['alpha'] = alphas
coef_df.set_index('alpha')
```

Out[37]:

	age	sex	bmi	bp	s1	s2	s3	s4	s5
alpha									
0.0000	-9.160885	-205.462260	516.684624	340.627341	-895.543609	561.214533	153.884786	126.734316	861.121400
0.0001	-9.118336	-205.337133	516.880570	340.556792	-883.415291	551.553259	148.578680	125.355917	856.480254
0.0010	-8.763583	-204.321125	518.371729	339.975385	-787.690766	475.274718	106.786540	114.632063	819.739542
0.0100	-6.401088	-198.669767	522.048548	336.348363	-383.709187	152.663678	-66.060583	75.611090	659.869402
0.1000	6.642753	-172.242166	485.523872	314.682122	-72.939323	-80.590053	-174.466515	83.616653	484.363285
1.0000	42.242217	-57.305508	282.170831	198.061386	14.363544	-22.551274	-136.930053	102.023193	260.104308
10.0000	21.174004	1.659796	63.659772	48.493240	18.421492	12.875448	-38.915435	38.842464	61.612405
100.0000	2.858979	0.629452	7.540604	5.849997	2.710879	2.142134	-4.834047	5.108223	7.448466
1000.0000	0.295726	0.069290	0.769004	0.597829	0.282900	0.225936	-0.495607	0.527031	0.761497
10000.0000	0.029674	0.006995	0.077054	0.059915	0.028412	0.022715	-0.049686	0.052870	0.076321

In []: