Lab Course Machine Learning

Exercise Sheet 3

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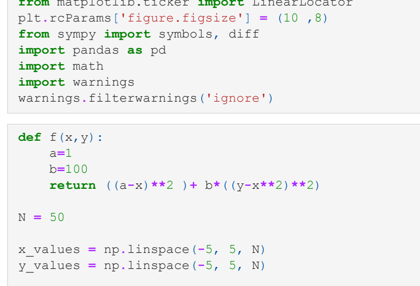
Exercise 1: Gradient Descent on Rosenbrock function

1. Implement a 3D plot to visualize the function

In [1]:
```python
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import cm
from matplotlib.ticker import LinearLocator
plt.rcParams['figure.figsize'] = (10 ,8)
from sympy import symbols, diff
import pandas as pd
import math
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```python
def f(x,y):
    a=1
    b=100
    return ((a-x)**2 )+ b*((y-x**2)**2)

N = 50

x_values = np.linspace(-5, 5, N)
y_values = np.linspace(-5, 5, N)

# creates grif
X, Y = np.meshgrid(x_values, y_values)

Z = f(X, Y)

ax = plt.axes(projection='3d')
ax.plot_surface(X, Y, Z, rstride=1, cstride=1,
                cmap=cm.coolwarm_r, edgecolor='none');
```



2. Derive the partial gradients.

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

Partial gradient:

$\frac{\partial f}{\partial x} = 2(x-a) - 4bx(y-x^2)$

$\frac{\partial f}{\partial y} = 2b(y-x^2)$

3. Convert the function and gradient of this function into equivalent code representation.

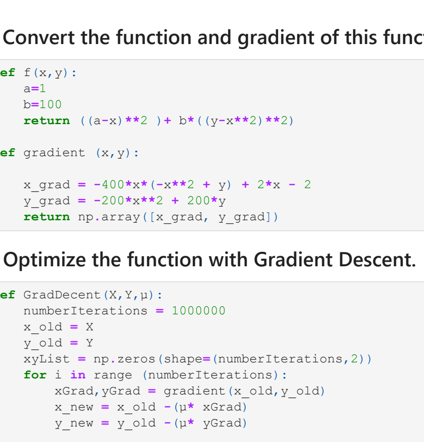
In [4]:
```python
def f(x,y):
    a=1
    b=100
    return ((a-x)**2 )+ b*((y-x**2)**2)

def gradient (x,y):

    x_grad = -400*x*(-x**2 + y) + 2*x - 2
    y_grad = -200*x**2 + 200*y
    return np.array([x_grad, y_grad])
```

4. Optimize the function with Gradient Descent.

In [5]:
```python
def GradDecent(X,Y,µ):
    numberIterations = 1000000
    x_old = X
    y_old = Y
    xyList = np.zeros(shape=(numberIterations,2))
    for i in range (numberIterations):
        xGrad,yGrad = gradient(x_old,y_old)
        x_new = x_old -(µ* xGrad)
        y_new = y_old -(µ* yGrad)

        xyList[i] = [x_old,y_old]
        x_old = x_new
        y_old = y_new

    return xyList
```

5. Visualize the trajectory on the same 3D plot.

In [6]:
```python
xy = GradDecent(2,2,0.000001)

zz = f(xy[:,0], xy[:,1])
N = 50

x_values = np.linspace(-5, 5, N)
y_values = np.linspace(-5, 5, N)

# creates grif
X, Y = np.meshgrid(x_values, y_values)

Z = f(X, Y)

# data for the scatter
xx = xy[:,0]
yy = xy[:,1]
zz = f(xx,yy)
fig = plt.figure(figsize=(14,10))
ax = plt.axes(projection='3d')

ax.view_init(elev=10., azim=80.)


ax.plot_surface(X, Y, Z, rstride=1, cstride=1,cmap='viridis', edgecolor='none')
ax.plot(xx, yy, zz, 'ro', alpha=0.5) # note the 'ro' (no '-') and the alpha
plt.show()
```



Exercise 1: Gradient Descent on Rosenbrock function

In [139...
```python
adf = pd.read_fwf('datasets/airq402.data',sep = ' ',header=None,names=["City1", "City2", "Average Fare", "Dista
adf.head()
```

Out[139...

	City1	City2	Average Fare	Distance	Average weekly passengers	market leading airline	market share	Average fare	Low price airline	market share2	price
0	CAK	ATL	114.47	528	424.56	FL	70.19	111.03	FL	70.19	111.03
1	CAK	MCO	122.47	860	276.84	FL	75.10	123.09	DL	17.23	118.94
2	ALB	ATL	214.42	852	215.76	DL	78.89	223.98	CO	2.77	167.12
3	ALB	BWI	69.40	288	606.84	WN	96.97	68.86	WN	96.97	68.86
4	ALB	ORD	158.13	723	313.04	UA	39.79	161.36	WN	15.34	145.42

In [140...
```python
cdf = pd.read_csv('datasets/winequality-red.csv',sep = ';')
cdf.head()
```

Out[140...

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

In [141...
```python
pdf = pd.read_csv('datasets/parkinsons_updrs.data',sep = ',')
pdf.head()
```

Out[141...

	subject#	age	sex	test_time	motor_UPDRS	total_UPDRS	Jitter(%)	Jitter(Abs)	Jitter:RAP	Jitter:PPQ5	...	Shimmer(dB)	Shimmer:APQ3
0	1	72	0	5.6431	28.199	34.398	0.00662	0.000034	0.00401	0.00317	...	0.230	0.01438
1	1	72	0	12.6660	28.447	34.894	0.00300	0.000017	0.00132	0.00150	...	0.179	0.00994
2	1	72	0	19.6810	28.695	35.389	0.00481	0.000025	0.00205	0.00208	...	0.181	0.00734
3	1	72	0	25.6470	28.905	35.810	0.00528	0.000027	0.00191	0.00264	...	0.327	0.01106
4	1	72	0	33.6420	29.187	36.375	0.00335	0.000020	0.00093	0.00130	...	0.176	0.00679

5 rows × 22 columns

4. Are there any columns that can be dropped? if so, which ones are why.

Wine Quality

In [142...
```python
cdf_cor = cdf.corr(method='pearson')
cdf_cor
```

Out[142...

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
fixed acidity	1.000000	-0.256131	0.671703	0.114777	0.093705	-0.153794	-0.113181	0.668047	-0.682978	0.183006	-0.061668	0.124052
volatile acidity	-0.256131	1.000000	-0.552496	0.001918	0.061298	-0.010504	0.076470	0.022026	0.234937	-0.260987	-0.202288	-0.390558
citric acid	0.671703	-0.552496	1.000000	0.143577	0.203823	-0.060978	0.035533	0.364947	-0.541904	0.312770	0.109903	0.226373
residual sugar	0.114777	0.001918	0.143577	1.000000	0.055610	0.187049	0.203028	0.355283	-0.085652	0.005527	0.042075	0.013732
chlorides	0.093705	0.061298	0.203823	0.055610	1.000000	0.005562	0.047400	0.200632	-0.265026	0.371260	-0.221141	-0.128907
free sulfur dioxide	-0.153794	-0.010504	-0.060978	0.187049	0.005562	1.000000	0.667666	-0.021946	0.070377	0.051658	-0.069408	-0.050656
total sulfur dioxide	-0.113181	0.076470	0.035533	0.203028	0.047400	0.667666	1.000000	0.071269	-0.066495	0.042947	-0.205654	-0.185100
density	0.668047	0.022026	0.364947	0.355283	0.200632	-0.021946	0.071269	1.000000	-0.341699	0.148506	-0.496180	-0.174919
pH	-0.682978	0.234937	-0.541904	-0.085652	-0.265026	0.070377	-0.066495	-0.341699	1.000000	-0.196648	0.205633	-0.057731
sulphates	0.183006	-0.260987	0.312770	0.005527	0.371260	0.051658	0.042947	0.148506	-0.196648	1.000000	0.093595	0.251397
alcohol	-0.061668	-0.202288	0.109903	0.042075	-0.221141	-0.069408	-0.205654	-0.496180	0.205633	0.093595	1.000000	0.476166
quality	0.124052	-0.390558	0.226373	0.013732	-0.128907	-0.050656	-0.185100	-0.174919	-0.057731	0.251397	0.476166	1.000000

In [143...
```python
cdf_cor.query('quality < 0.2 and quality>-0.2')
```

Out[143...

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
fixed acidity	1.000000	-0.256131	0.671703	0.114777	0.093705	-0.153794	-0.113181	0.668047	-0.682978	0.183006	-0.061668	0.124052
residual sugar	0.114777	0.001918	0.143577	1.000000	0.055610	0.187049	0.203028	0.355283	-0.085652	0.005527	0.042075	0.013732
chlorides	0.093705	0.061298	0.203823	0.055610	1.000000	0.005562	0.047400	0.200632	-0.265026	0.371260	-0.221141	-0.128907
free sulfur dioxide	-0.153794	-0.010504	-0.060978	0.187049	0.005562	1.000000	0.667666	-0.021946	0.070377	0.051658	-0.069408	-0.050656
total sulfur dioxide	-0.113181	0.076470	0.035533	0.203028	0.047400	0.667666	1.000000	0.071269	-0.066495	0.042947	-0.205654	-0.185100
density	0.668047	0.022026	0.364947	0.355283	0.200632	-0.021946	0.071269	1.000000	-0.341699	0.148506	-0.496180	-0.174919
pH	-0.682978	0.234937	-0.541904	-0.085652	-0.265026	0.070377	-0.066495	-0.341699	1.000000	-0.196648	0.205633	-0.057731

These above columns can be droped because these have very week corelation.

Air Quality

In [144...
```python
adf_cor = adf.corr(method='pearson')
adf_cor
```

Out[144...

	Average Fare	Distance	Average weekly passengers	market share	Average fare	market share2	price
Average Fare	1.000000	0.587169	-0.126175	-0.234142	0.981462	-0.458660	0.866410
Distance	0.587169	1.000000	-0.090131	-0.531406	0.564082	-0.367831	0.583239
Average weekly passengers	-0.126175	-0.090131	1.000000	-0.067605	-0.100946	0.034241	-0.142314
market share	-0.234142	-0.531406	-0.067605	1.000000	-0.220801	0.306832	-0.307672
Average fare	0.981462	0.564082	-0.100946	-0.220801	1.000000	-0.472838	0.826511
market share2	-0.458660	-0.367831	0.034241	0.306832	-0.472838	1.000000	-0.240186
price	0.866410	0.583239	-0.142314	-0.307672	0.826511	-0.240186	1.000000

In [145...
```python
adf_cor.query('price < 0.2 and price>-0.2')
```

Out[145...

	Average Fare	Distance	Average weekly passengers	market share	Average fare	market share2	price
Average weekly passengers	-0.126175	-0.090131	1.0	-0.067605	-0.100946	0.034241	-0.142314

In [ ]:
```
These above columns can be droped because these have very week corelation.
```

Parkisons Dataset

In [146...
```python
pdf_cor = pdf.corr(method='pearson')
pdf_cor
```

Out[146...

	subject#	age	sex	test_time	motor_UPDRS	total_UPDRS	Jitter(%)	Jitter(Abs)	Jitter:RAP	Jitter:PPQ5	...
subject#	1.000000	-0.030864	0.286851	-0.000882	0.252919	0.253643	0.135448	0.075156	0.120339	0.136474	...
age	-0.030864	1.000000	-0.041602	0.019884	0.273665	0.310290	0.023071	0.035691	0.010255	0.013199	...
sex	0.286851	-0.041602	1.000000	-0.009805	-0.031205	-0.096559	0.051422	-0.154645	0.076718	0.087995	...
test_time	-0.000882	0.019884	-0.009805	1.000000	0.067918	0.075263	-0.022837	-0.011365	-0.028888	-0.023290	...
motor_UPDRS	0.252919	0.273665	-0.031205	0.067918	1.000000	0.947231	0.084816	0.050903	0.072684	0.076291	...
total_UPDRS	0.253643	0.310290	-0.096559	0.075263	0.947231	1.000000	0.074247	0.066927	0.064015	0.063352	...
Jitter(%)	0.135448	0.023071	0.051422	-0.022837	0.084816	0.074247	1.000000	0.865577	0.984181	0.968214	...
Jitter(Abs)	0.075156	0.035691	-0.154645	-0.011365	0.050903	0.066927	0.865577	1.000000	0.844626	0.790538	...
Jitter:RAP	0.120339	0.010255	0.076718	-0.028888	0.072684	0.064015	0.984181	0.844626	1.000000	0.947196	...
Jitter:PPQ5	0.136474	0.013199	0.087995	-0.023290	0.076291	0.063352	0.968214	0.790538	0.947196	1.000000	...
Jitter:DDP	0.120350	0.010258	0.076703	-0.028876	0.072698	0.064027	0.984184	0.844630	1.000000	0.947203	...
Shimmer	0.146202	0.101554	0.058736	-0.033870	0.102349	0.092141	0.709791	0.649046	0.681729	0.732747	...
Shimmer(dB)	0.142864	0.111130	0.056481	-0.030962	0.110076	0.098790	0.716704	0.655871	0.685551	0.734591	...
Shimmer:APQ3	0.112950	0.098912	0.044937	-0.029020	0.084261	0.079363	0.664149	0.623830	0.650226	0.676711	...
Shimmer:APQ5	0.138264	0.089983	0.064819	-0.036504	0.092105	0.083467	0.694002	0.621401	0.659831	0.734021	...
Shimmer:APQ11	0.173333	0.135238	0.023360	-0.039110	0.136560	0.120838	0.645965	0.589998	0.603082	0.668413	...
Shimmer:DDA	0.112949	0.098913	0.044938	-0.029017	0.084260	0.079363	0.664147	0.623827	0.650225	0.676710	...
NHR	0.168743	0.007093	0.168170	-0.026357	0.074967	0.060952	0.825294	0.699960	0.792373	0.864864	...
HNR	-0.206929	-0.104842	-0.000167	0.036545	-0.157029	-0.162117	-0.675188	-0.706418	-0.641473	-0.662409	...
RPDE	0.147300	0.090208	-0.159262	-0.038887	0.128607	0.156897	0.427128	0.547100	0.382891	0.381503	...
DFA	0.097464	-0.092870	-0.165113	0.019261	-0.116242	-0.113475	0.226550	0.352264	0.214881	0.175359	...
PPE	0.157559	0.120790	-0.099901	-0.000563	0.162433	0.156195	0.721849	0.787853	0.670652	0.663491	...

22 rows × 22 columns

In [147...
```python
pdf_cor.query('total_UPDRS < 0.2 and total_UPDRS>-0.2')
```

Out[147...

	subject#	age	sex	test_time	motor_UPDRS	total_UPDRS	Jitter(%)	Jitter(Abs)	Jitter:RAP	Jitter:PPQ5	...
sex	0.286851	-0.041602	1.000000	-0.009805	-0.031205	-0.096559	0.051422	-0.154645	0.076718	0.087995	...
test_time	-0.000882	0.019884	-0.009805	1.000000	0.067918	0.075263	-0.022837	-0.011365	-0.028888	-0.023290	...
Jitter(%)	0.135448	0.023071	0.051422	-0.022837	0.084816	0.074247	1.000000	0.865577	0.984181	0.968214	...
Jitter(Abs)	0.075156	0.035691	-0.154645	-0.011365	0.050903	0.066927	0.865577	1.000000	0.844626	0.790538	...
Jitter:RAP	0.120339	0.010255	0.076718	-0.028888	0.072684	0.064015	0.984181	0.844626	1.000000	0.947196	...
Jitter:PPQ5	0.136474	0.013199	0.087995	-0.023290	0.076291	0.063352	0.968214	0.790538	0.947196	1.000000	...
Jitter:DDP	0.120350	0.010258	0.076703	-0.028876	0.072698	0.064027	0.984184	0.844630	1.000000	0.947203	...
Shimmer	0.146202	0.101554	0.058736	-0.033870	0.102349	0.092141	0.709791	0.649046	0.681729	0.732747	...
Shimmer(dB)	0.142864	0.111130	0.056481	-0.030962	0.110076	0.098790	0.716704	0.655871	0.685551	0.734591	...
Shimmer:APQ3	0.112950	0.098912	0.044937	-0.029020	0.084261	0.079363	0.664149	0.623830	0.650226	0.676711	...
Shimmer:APQ5	0.138264	0.089983	0.064819	-0.036504	0.092105	0.083467	0.694002	0.621401	0.659831	0.734021	...
Shimmer:APQ11	0.173333	0.135238	0.023360	-0.039110	0.136560	0.120838	0.645965	0.589998	0.603082	0.668413	...
Shimmer:DDA	0.112949	0.098913	0.044938	-0.029017	0.084260	0.079363	0.664147	0.623827	0.650225	0.676710	...
NHR	0.168743	0.007093	0.168170	-0.026357	0.074967	0.060952	0.825294	0.699960	0.792373	0.864864	...
HNR	-0.206929	-0.104842	-0.000167	0.036545	-0.157029	-0.162117	-0.675188	-0.706418	-0.641473	-0.662409	...
RPDE	0.147300	0.090208	-0.159262	-0.038887	0.128607	0.156897	0.427128	0.547100	0.382891	0.381503	...
DFA	0.097464	-0.092870	-0.165113	0.019261	-0.116242	-0.113475	0.226550	0.352264	0.214881	0.175359	...
PPE	0.157559	0.120790	-0.099901	-0.000563	0.162433	0.156195	0.721849	0.787853	0.670652	0.663491	...

18 rows × 22 columns

In [ ]:
```
These above columns can be droped because these have very week corelation.
```

1. Convert any non-numeric values to numeric values.

In [12]:
```python
adf = pd.get_dummies(adf)
```

In [13]:
```python
cdf = pd.get_dummies(cdf)
```

In [14]:
```python
pdf = pd.get_dummies(pdf)
```

2 . If required drop out the rows with missing values or NA. In next lectures we will handle sparse data, which will allow us to use records with missing values.

In [21]:
```python
is_NaN = adf.isnull()
row_has_NaN = is_NaN.any(axis=1)
rows_with_NaN = adf[row_has_NaN]
rows_with_NaN
```

Out[21]:

Average Fare	Distance	Average weekly passengers	market share	Average fare	market share2	price	City1_ABQ	City1_ACY	City1_ALB	...	Low price airline_G4	Low price airline_HP	Low price airline_NK

0 rows × 217 columns

In [22]:
```python
is_NaN = cdf.isnull()
row_has_NaN = is_NaN.any(axis=1)
rows_with_NaN = cdf[row_has_NaN]
rows_with_NaN
```

Out[22]:

fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality

In [23]:
```python
is_NaN = pdf.isnull()
row_has_NaN = is_NaN.any(axis=1)
rows_with_NaN = pdf[row_has_NaN]
rows_with_NaN
```

Out[23]:

subject#	age	sex	test_time	motor_UPDRS	total_UPDRS	Jitter(%)	Jitter(Abs)	Jitter:RAP	Jitter:PPQ5	...	Shimmer(dB)	Shimmer:APQ3

0 rows × 22 columns

3. Split the dataset into 80% Train set and 20% Test set.

In [24]:
```python
adf_train = adf.loc[0:math.floor(len(adf)*0.8)]
adf_test = adf.loc[math.floor(len(adf)*0.8)+1:]
len(adf) == len(adf_train)+ len(adf_test)
adf_train.head()
```

Out[24]:

	Average Fare	Distance	Average weekly passengers	market share	Average fare	market share2	price	City1_ABQ	City1_ACY	City1_ALB	...	Low price airline_G4	Low price airline_HP	Low price airline_NK
0	114.47	528	424.56	70.19	111.03	70.19	111.03	0	0	0	...	0	0	0
1	122.47	860	276.84	75.10	123.09	17.23	118.94	0	0	0	...	0	0	0
2	214.42	852	215.76	78.89	223.98	2.77	167.12	0	0	1	...	0	0	0
3	69.40	288	606.84	96.97	68.86	96.97	68.86	0	0	1	...	0	0	0
4	158.13	723	313.04	39.79	161.36	15.34	145.42	0	0	1	...	0	0	0

5 rows × 217 columns

In [25]:
```python
cdf_train = cdf.loc[0:math.floor(len(cdf)*0.8)]
cdf_test = cdf.loc[math.floor(len(cdf)*0.8)+1:]
len(cdf) == len(cdf_train)+ len(cdf_test)
cdf_train.head()
```

Out[25]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

In [30]:
```python
pdf_train = pdf.loc[0:math.floor(len(pdf)*0.8)]
pdf_test = pdf.loc[math.floor(len(pdf)*0.8)+1:]
len(pdf) == len(pdf_train)+ len(pdf_test)
pdf_train.head()
```

Out[30]:

	subject#	age	sex	test_time	motor_UPDRS	total_UPDRS	Jitter(%)	Jitter(Abs)	Jitter:RAP	Jitter:PPQ5	...	Shimmer(dB)	Shimmer:APQ3
0	1	72	0	5.6431	28.199	34.398	0.00662	0.000034	0.00401	0.00317	...	0.230	0.01438
1	1	72	0	12.6660	28.447	34.894	0.00300	0.000017	0.00132	0.00150	...	0.179	0.00994
2	1	72	0	19.6810	28.695	35.389	0.00481	0.000025	0.00205	0.00208	...	0.181	0.00734
3	1	72	0	25.6470	28.905	35.810	0.00528	0.000027	0.00191	0.00264	...	0.327	0.01106
4	1	72	0	33.6420	29.187	36.375	0.00335	0.000020	0.00093	0.00130	...	0.176	0.00679

5 rows × 22 columns

Part B: Linear Regression with Real-World Data

In [31]:
```python
def loss(X,Y,B):
    sum = 0
    for i in range (len(X)):
        sum  = sum +((Y[i].T-np.dot(X[i],B)) ** 2)
    return sum

def lossGrad(X,Y,B):
    gradiant = np.zeros(len(X[0]))

    for i in range (len(X[0])):
        sum = 0
        for j in range(len(X)):

            sum  = sum +((-2)*(Y[j].T-np.dot(X[j],B)) * X[j][i])
        gradiant[i] = sum
    return gradiant
def RMSE(x_test,y_test,B):
    rmse = 0
    for i in range (len(x_test)):
        rmse = rmse + (y_test[i]-np.dot(x_test[i],B))**2
    rmse  = np.sqrt(rmse/len(x_test))
    return rmse



def GradDecent(X,Y,µ,B,xtest,ytest):
    B_old = np.zeros(len(X[0]))
    numberIterations = 600
    fold__min_fnew_List = np.zeros(numberIterations)
    rmse_List = np.zeros(numberIterations)
    for i in range (numberIterations):
        B_new = B_old - (µ* lossGrad(X,Y,B_old))
        fold__min_fnew_List[i]= abs(loss(X,Y,B_old)-loss(X,Y,B_new))
        rmse_List[i] = RMSE(xtest,ytest,B_old)
        B_old = B_new


    return B_old,fold__min_fnew_List,rmse_List
```

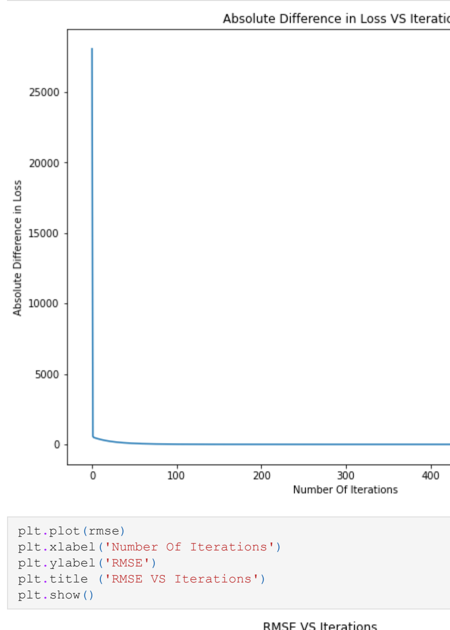
µ = 10**(-7)

Wine Quality Dataset

In [149...
```python
X_train = cdf_train.loc[:, cdf_train.columns != 'quality']
Y_train = cdf_train[['quality']]
X_test = (cdf_train.loc[:, cdf_train.columns != 'quality']).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))

X_test = np.append(bias_column,X_test,axis=1)
Y_test = (cdf_train[['quality']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))

µ = 10**(-7)
B,fold__min_fnew_List,rmse = GradDecent(X,Y,µ,B,X_test,Y_test)
```

In [34]:
```python
plt.plot(fold__min_fnew_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('Absolute Difference in Loss')
plt.title ('Absolute Difference in Loss VS Iterations')
plt.show()
```

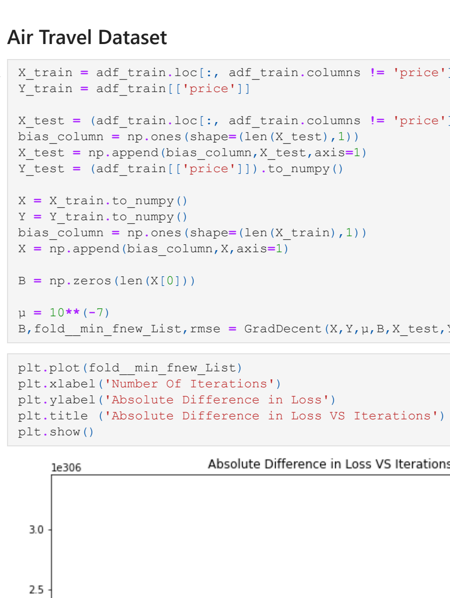
In [35]:
```python
plt.plot(rmse)
plt.xlabel('Number Of Iterations')
plt.ylabel('RMSE')
plt.title ('RMSE VS Iterations')
plt.show()
```



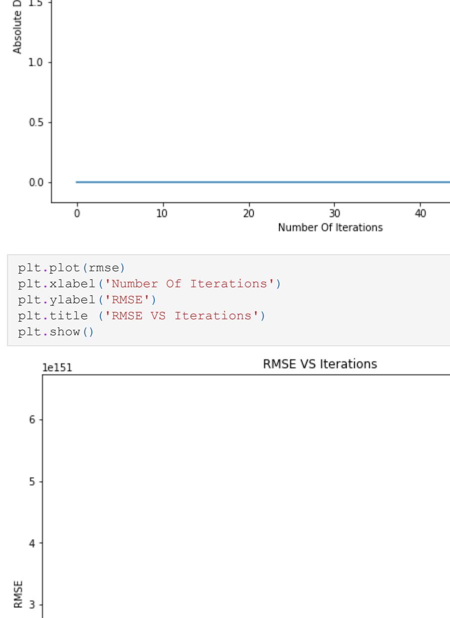
Air Travel Dataset

In [150...
```python
X_train = adf_train.loc[:, adf_train.columns != 'price']
Y_train = adf_train[['price']]

X_test = (adf_train.loc[:, adf_train.columns != 'price']).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))
X_test = np.append(bias_column,X_test,axis=1)
Y_test = (adf_train[['price']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))

µ = 10**(-7)
B,fold__min_fnew_List,rmse = GradDecent(X,Y,µ,B,X_test,Y_test)
```

In [37]:
```python
plt.plot(fold__min_fnew_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('Absolute Difference in Loss')
plt.title ('Absolute Difference in Loss VS Iterations')
plt.show()
```



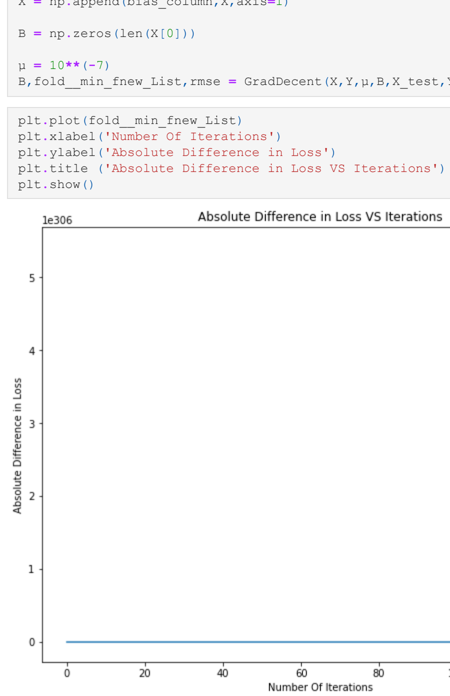
In [38]:
```python
plt.plot(rmse)
plt.xlabel('Number Of Iterations')
plt.ylabel('RMSE')
plt.title ('RMSE VS Iterations')
plt.show()
```



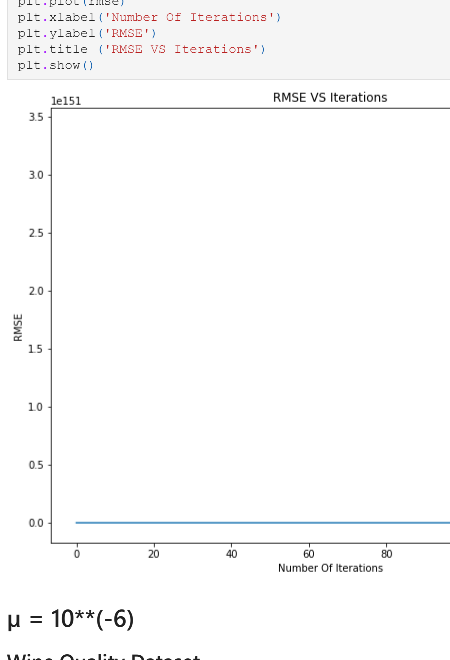
Parkinsons Dataset

In [39]:
```python
X_train = pdf_train.loc[:, pdf_train.columns != 'total_UPDRS']
Y_train = pdf_train[['total_UPDRS']]

X_test = (pdf_train.loc[:, pdf_train.columns != 'total_UPDRS']).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))
X_test = np.append(bias_column,X_test,axis=1)
Y_test = (pdf_train[['total_UPDRS']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))

µ = 10**(-7)
B,fold__min_fnew_List,rmse = GradDecent(X,Y,µ,B,X_test,Y_test)
```

In [40]:
```python
plt.plot(fold__min_fnew_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('Absolute Difference in Loss')
plt.title ('Absolute Difference in Loss VS Iterations')
plt.show()
```



In [41]:
```python
plt.plot(rmse)
plt.xlabel('Number Of Iterations')
plt.ylabel('RMSE')
plt.title ('RMSE VS Iterations')
plt.show()
```

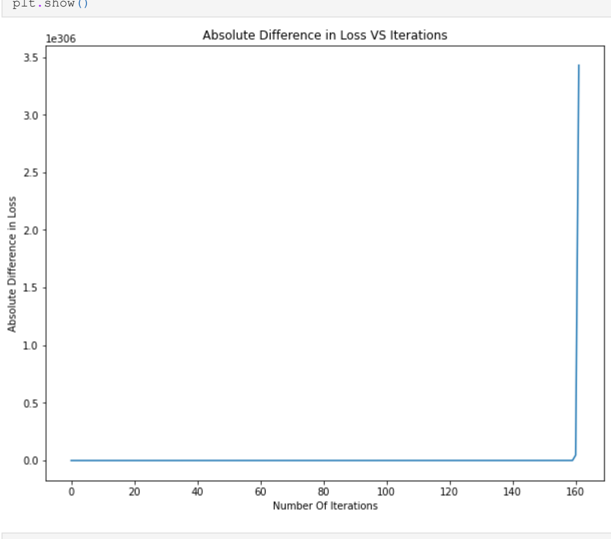


µ = 10**(-6)

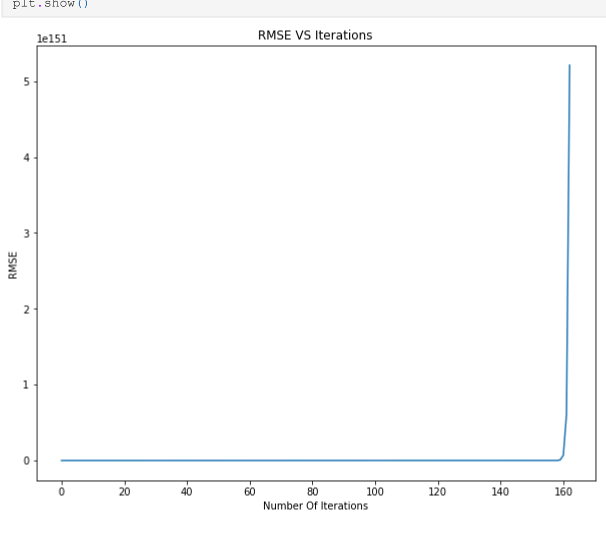
Wine Quality Dataset

```
In [151…: X_train = cdf_train.loc[:, cdf_train.columns != 'quality']
Y_train = cdf_train[['quality']]
X_test = (cdf_train.loc[:, cdf_train.columns != 'quality']).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))

X_test = np.append(bias_column,X_test,axis=1)
Y_test = (cdf_train[['quality']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))

µ = 10**(-6)
B,fold__min_fnew_List,rmse = GradDecent(X,Y,µ,B,X_test,Y_test)
```

```
In [152…: plt.plot(fold__min_fnew_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('Absolute Difference in Loss')
plt.title ('Absolute Difference in Loss VS Iterations')
plt.show()
```



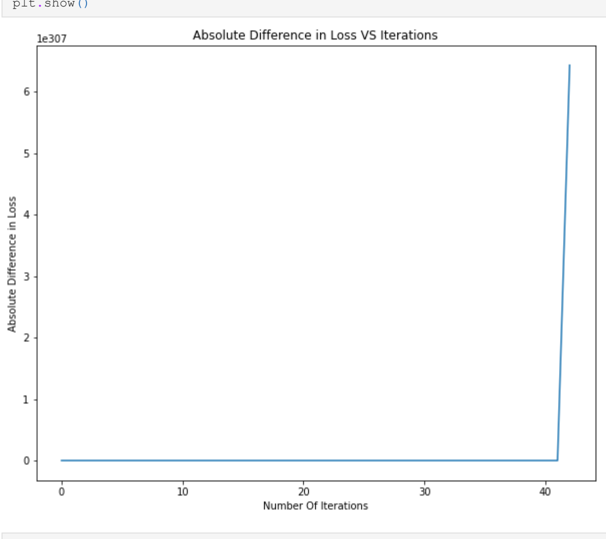

```
In [153…: plt.plot(rmse)
plt.xlabel('Number Of Iterations')
plt.ylabel('RMSE')
plt.title ('RMSE VS Iterations')
plt.show()
```



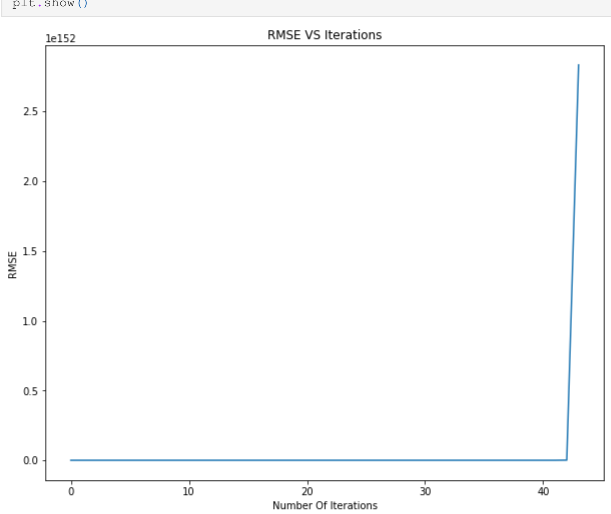
Air Travel Dataset

```
In [154…: X_train = adf_train.loc[:, adf_train.columns != 'price']
Y_train = adf_train[['price']]

X_test = (adf_train.loc[:, adf_train.columns != 'price']).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))
X_test = np.append(bias_column,X_test,axis=1)
Y_test = (adf_train[['price']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))

µ = 10**(-6)
B,fold__min_fnew_List,rmse = GradDecent(X,Y,µ,B,X_test,Y_test)
```

```
In [155…: plt.plot(fold__min_fnew_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('Absolute Difference in Loss')
plt.title ('Absolute Difference in Loss VS Iterations')
plt.show()
```



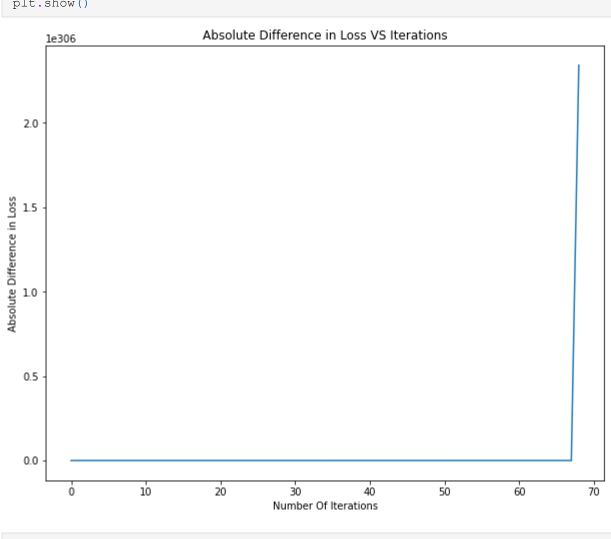

```
In [156…: plt.plot(rmse)
plt.xlabel('Number Of Iterations')
plt.ylabel('RMSE')
plt.title ('RMSE VS Iterations')
plt.show()
```



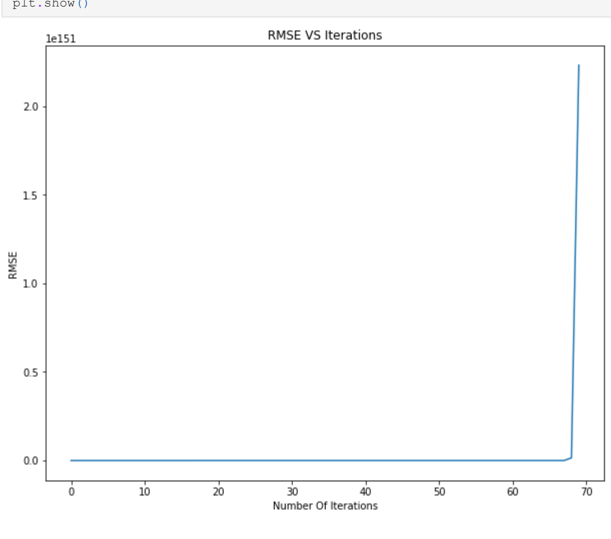
Parkinsons Dataset

```
In [157…: X_train = pdf_train.loc[:, pdf_train.columns != 'total_UPDRS']
Y_train = pdf_train[['total_UPDRS']]

X_test = (pdf_train.loc[:, pdf_train.columns != 'total_UPDRS']).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))
X_test = np.append(bias_column,X_test,axis=1)
Y_test = (pdf_train[['total_UPDRS']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))

µ = 10**(-6)
B,fold__min_fnew_List,rmse = GradDecent(X,Y,µ,B,X_test,Y_test)
```

```
In [158…: plt.plot(fold__min_fnew_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('Absolute Difference in Loss')
plt.title ('Absolute Difference in Loss VS Iterations')
plt.show()
```




```
In [159…: plt.plot(rmse)
plt.xlabel('Number Of Iterations')
plt.ylabel('RMSE')
plt.title ('RMSE VS Iterations')
plt.show()
```

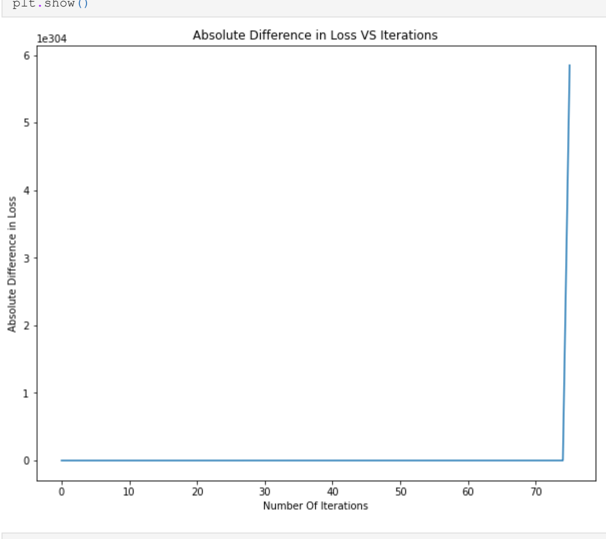


µ = 10**(-5)

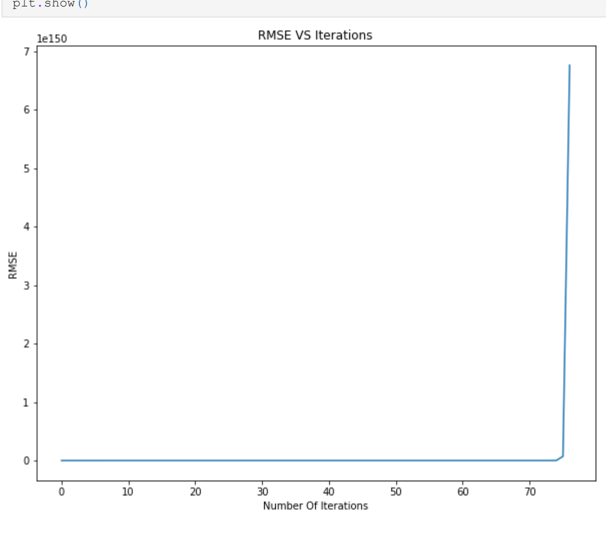
Wine Quality Dataset

```
In [160…: X_train = cdf_train.loc[:, cdf_train.columns != 'quality']
Y_train = cdf_train[['quality']]
X_test = (cdf_train.loc[:, cdf_train.columns != 'quality']).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))

X_test = np.append(bias_column,X_test,axis=1)
Y_test = (cdf_train[['quality']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))

µ = 10**(-5)
B,fold__min_fnew_List,rmse = GradDecent(X,Y,µ,B,X_test,Y_test)
```

```
In [161…: plt.plot(fold__min_fnew_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('Absolute Difference in Loss')
plt.title ('Absolute Difference in Loss VS Iterations')
plt.show()
```




```
In [162…: plt.plot(rmse)
plt.xlabel('Number Of Iterations')
plt.ylabel('RMSE')
plt.title ('RMSE VS Iterations')
plt.show()
```



Air Travel Dataset

```
In [ ]: X_train = adf_train.loc[:, adf_train.columns != 'price']
Y_train = adf_train[['price']]

X_test = (adf_train.loc[:, adf_train.columns != 'price']).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))
X_test = np.append(bias_column,X_test,axis=1)
Y_test = (adf_train[['price']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))

µ = 10**(-5)
B,fold__min_fnew_List,rmse = GradDecent(X,Y,µ,B,X_test,Y_test)
```

```
In [ ]: plt.plot(fold__min_fnew_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('Absolute Difference in Loss')
plt.title ('Absolute Difference in Loss VS Iterations')
plt.show()
```

```
In [ ]: plt.plot(rmse)
plt.xlabel('Number Of Iterations')
plt.ylabel('RMSE')
plt.title ('RMSE VS Iterations')
plt.show()
```

Parkinsons Dataset

```
In [ ]: X_train = pdf_train.loc[:, pdf_train.columns != 'total_UPDRS']
Y_train = pdf_train[['total_UPDRS']]

X_test = (pdf_train.loc[:, pdf_train.columns != 'total_UPDRS']).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))
X_test = np.append(bias_column,X_test,axis=1)
Y_test = (pdf_train[['total_UPDRS']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))

µ = 10**(-5)
B,fold__min_fnew_List,rmse = GradDecent(X,Y,µ,B,X_test,Y_test)
```

```
In [ ]: plt.plot(fold__min_fnew_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('Absolute Difference in Loss')
plt.title ('Absolute Difference in Loss VS Iterations')
plt.show()
```

```
In [ ]: plt.plot(rmse)
plt.xlabel('Number Of Iterations')
plt.ylabel('RMSE')
plt.title ('RMSE VS Iterations')
plt.show()
```

Exercise 3: Steplength Control for Gradient Descent

1. steplength-backtracking

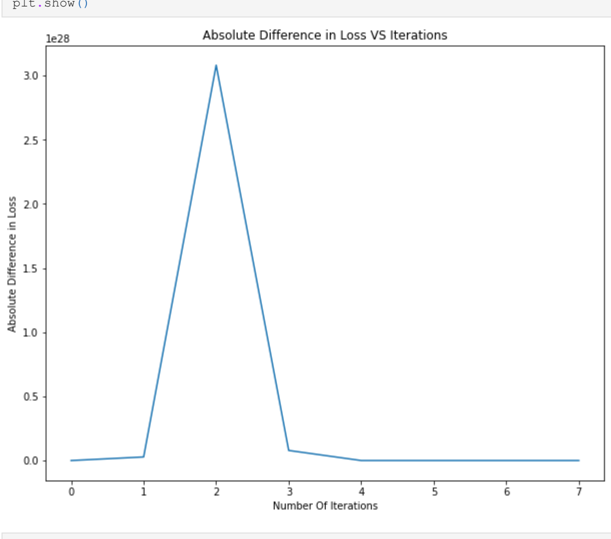
```
In [70]: def stepLengthBacktracking(X,Y,B_old,xtest,ytest):
    µ =1
    ß = 0.0011
    a = 0.005
    B_new = B_old -(µ* lossGrad(X,Y,B_old))
    i= 0
    fold__min_fnew_List = []
    rmse_List = []
    while((loss(X,Y,B_new)) > (loss(X,Y,B_old) - (µ*a*np.dot(lossGrad(X,Y,B_old),lossGrad(X,Y,B_old))))):
        B_new = B_old (µ* lossGrad(X,Y,B_old))
        fold__min_fnew_List.append(abs(loss(X,Y,B_old)-loss(X,Y,B_new)))
        print(RMSE(xtest,ytest,B_old))
        rmse_List.append(RMSE(xtest,ytest,B_old)[0])
        B_old = B_new
        i += 1
        µ = µ*ß
    print (i)
    return fold__min_fnew_List,rmse_List,µ
```

Wine Quality Dataset

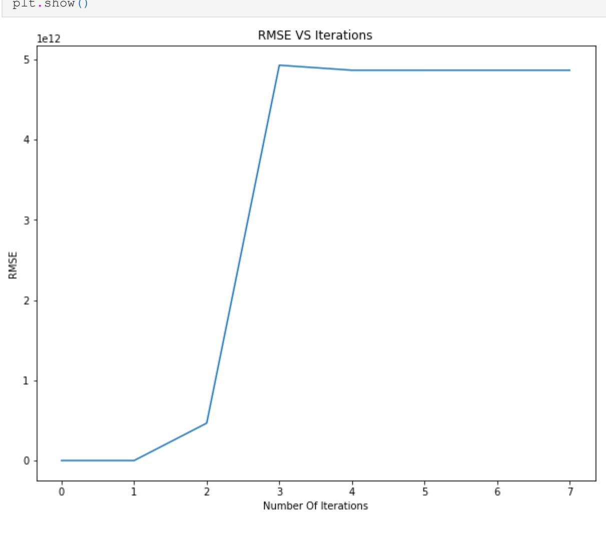
```
In [43]: cdf_train
X_train = cdf_train.loc[:, cdf_train.columns != 'quality']
Y_train = cdf_train[['quality']]

X_test = (cdf_train.loc[:, cdf_train.columns != 'quality']).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))
X_test = np.append(bias_column,X_test,axis=1)
Y_test = (cdf_train[['quality']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))
fold__min_fnew_List,rmse_List,µ= stepLengthBacktracking(X,Y,B,X_test,Y_test)
```

```
[5.72282983]
[44375614.27355857]
[4.66494021e+11]
[4.92900566e+12]
[4.86629554e+12]
[4.86622744e+12]
[4.86622736e+12]
[4.86622736e+12]
8
```

```
In [44]: plt.plot(fold__min_fnew_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('Absolute Difference in Loss')
plt.title ('Absolute Difference in Loss VS Iterations')
plt.show()
```




```
In [45]: plt.plot(rmse_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('RMSE')
plt.title ('RMSE VS Iterations')
plt.show()
```

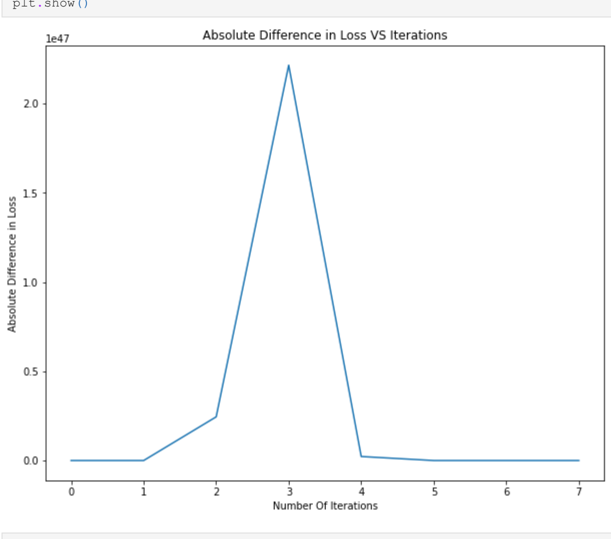


Air Travel Dataset

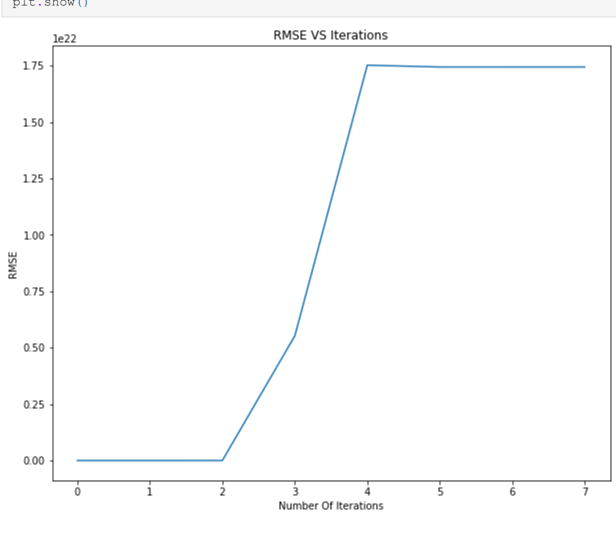
```
In [46]: X_train = adf_train.loc[:, adf_train.columns != 'price']
Y_train = adf_train[['price']]

X_test = (adf_train.loc[:, adf_train.columns != 'price']).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))
X_test = np.append(bias_column,X_test,axis=1)
Y_test = (adf_train[['price']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))
fold__min_fnew_List,rmse_List,µ= stepLengthBacktracking(X,Y,B,X_test,Y_test)
```

```
[151.03247514]
[4.23899403e+11]
[1.45834021e+18]
[5.52669217e+21]
[1.75214756e+22]
[1.74410973e+22]
[1.74410093e+22]
[1.74410092e+22]
8
```

```
In [47]: plt.plot(fold__min_fnew_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('Absolute Difference in Loss')
plt.title ('Absolute Difference in Loss VS Iterations')
plt.show()
```




```
In [48]: plt.plot(rmse_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('RMSE')
plt.title ('RMSE VS Iterations')
plt.show()
```

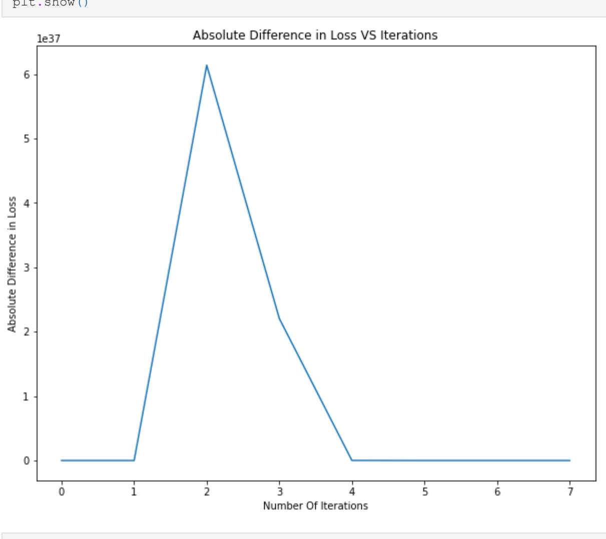


Parkinsons Dataset

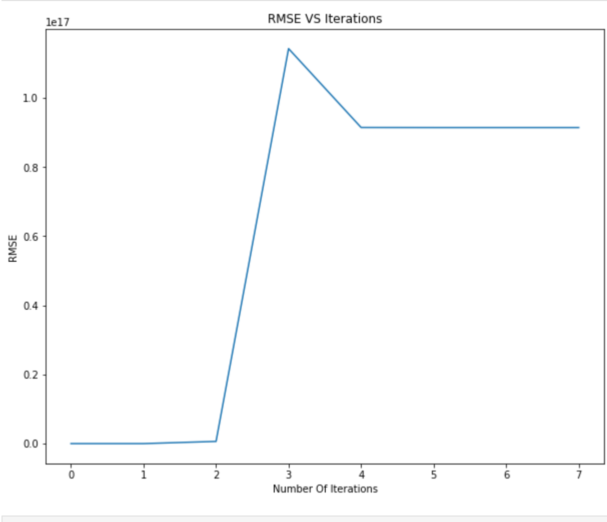
```
In [49]: X_train = pdf_train.loc[:, pdf_train.columns != 'total_UPDRS']
Y_train = pdf_train[['total_UPDRS']]

X_test = (pdf_train.loc[:, pdf_train.columns != 'total_UPDRS']).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))
X_test = np.append(bias_column,X_test,axis=1)
Y_test = (pdf_train[['total_UPDRS']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))
fold__min_fnew_List,rmse_List,µ= stepLengthBacktracking(X,Y,B,X_test,Y_test)
```

```
[28.77880161]
[3.8401614e+09]
[6.33242236e+14]
[1.14264404e+17]
[9.14586e+16]
[9.14385206e+16]
[9.14384985e+16]
[9.14384984e+16]
8
```

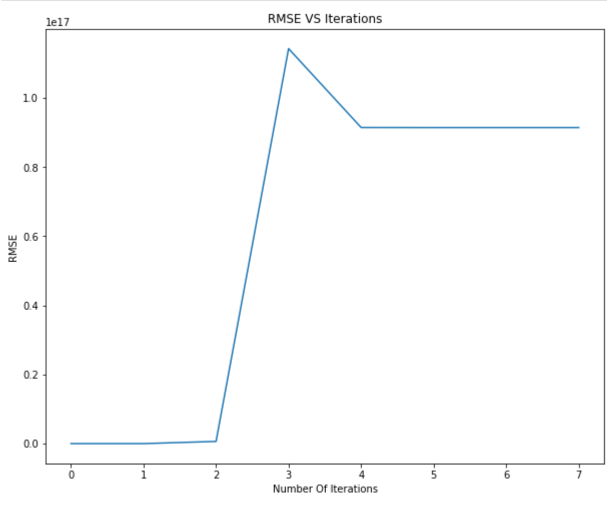
```
In [50]: plt.plot(fold__min_fnew_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('Absolute Difference in Loss')
plt.title ('Absolute Difference in Loss VS Iterations')
plt.show()
```




```
In [51]: plt.plot(rmse_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('RMSE')
plt.title ('RMSE VS Iterations')
plt.show()
```




```
In [51]: plt.plot(rmse_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('RMSE')
plt.title ('RMSE VS Iterations')
plt.show()
```



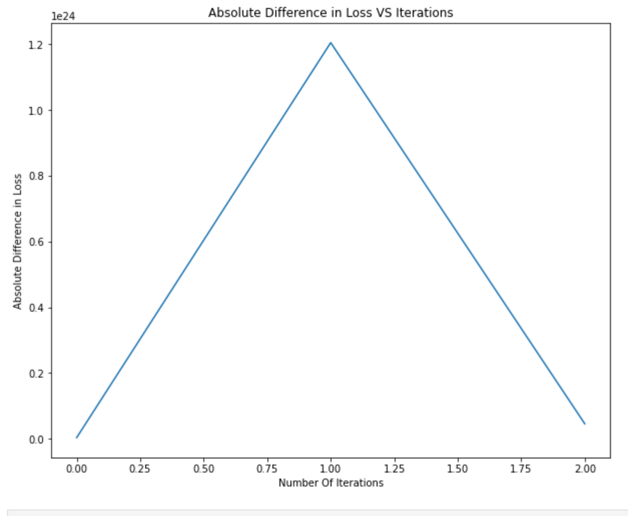
2. steplength-bolddriver

```
In [89]: def stepLengthBolddriver(X,Y,B_old,µ_old,µ_plus,µ_minus,xtest,ytest):
    µ =µ_old *µ_plus
    B_new = B_old -(µ* lossGrad(X,Y,B_old))
    i= 0
    fold__min_fnew_List = []
    rmse_List = []
    print('old',loss(X,Y,B_old))
    print('new',loss(X,Y,B_new))
    while((loss(X,Y,B_old) - (loss(X,Y,B_new))) <= 0):
        B_old = B_new
        B_new = B_old -(µ* lossGrad(X,Y,B_old))
        fold__min_fnew_List.append(abs(loss(X,Y,B_old)-loss(X,Y,B_new)))
        print(RMSE(xtest,ytest,B_old))
        rmse_List.append(RMSE(xtest,ytest,B_old)[0])
        i += 1
        µ = µ*µ_minus
        print (i)
    return fold__min_fnew_List,rmse_List,µ
```

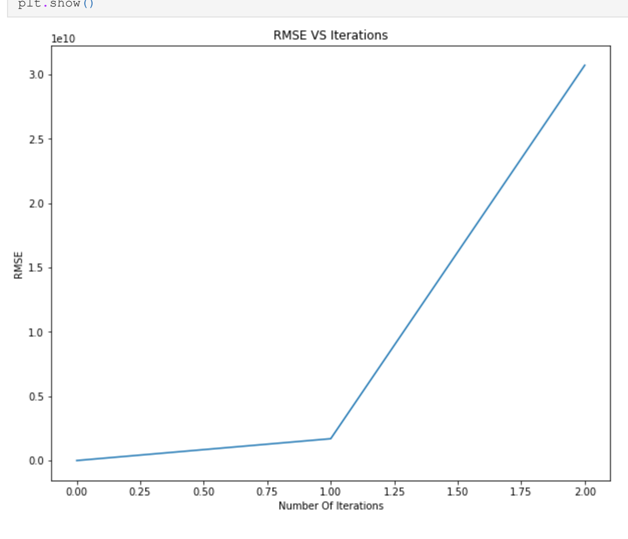
```
In [94]: cdf_train
X_train = cdf_train.loc[:, cdf_train.columns != 'quality']
Y_train = cdf_train[['quality']]

X_test = (cdf_train.loc[:, cdf_train.columns != 'quality']).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))
X_test = np.append(bias_column,X_test,axis=1)
Y_test = (cdf_train[['quality']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))
fold__min_fnew_List,rmse_List,µ= stepLengthBolddriver(X,Y,B,0.1,0.02,0.001,X_test,Y_test)
```

```
old [41921.]
new [1.00812159e+13]
[88746.54885269]
1
[1.69632594e+09]
2
[3.07331191e+10]
3
```

```
In [95]: plt.plot(fold__min_fnew_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('Absolute Difference in Loss')
plt.title ('Absolute Difference in Loss VS Iterations')
plt.show()
```



In [96]:
```
plt.plot(rmse_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('RMSE')
plt.title ('RMSE VS Iterations')
plt.show()
```

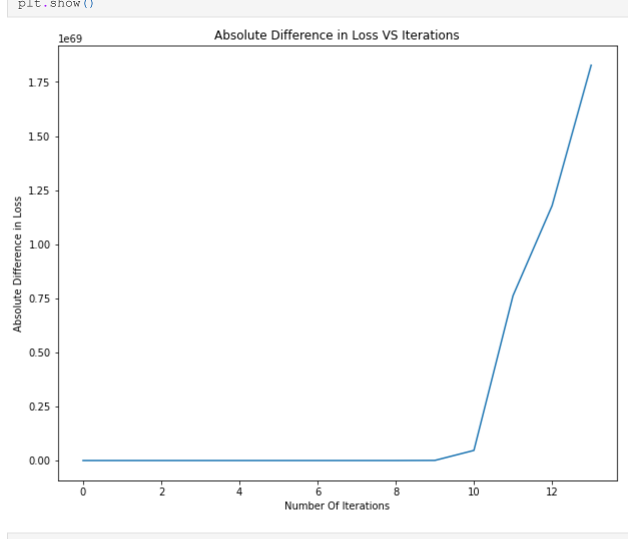


Wine Quality Dataset

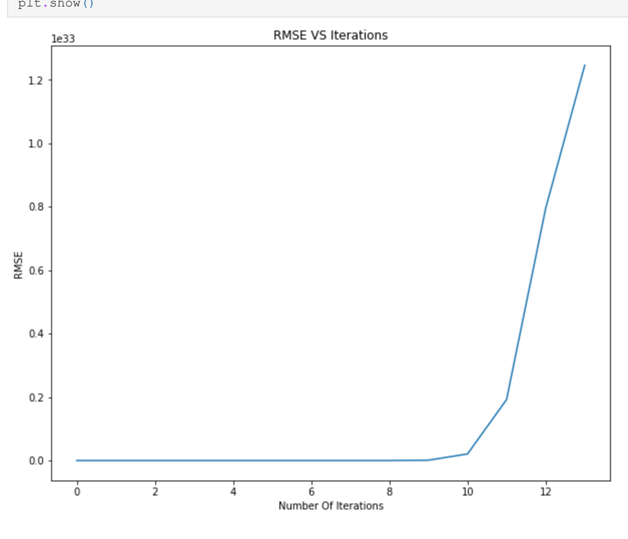
In [122…
```
cdf_train
X_train = cdf_train.loc[:, cdf_train.columns != 'quality']
Y_train = cdf_train[['quality']]

X_test = (cdf_train.loc[:, cdf_train.columns != 'quality']).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))
X_test = np.append(bias_column,X_test,axis=1)
Y_test = (cdf_train[['quality']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))
fold__min_fnew_List,rmse_List,μ= stepLengthBolddriver(X,Y,B,0.001,1.1,0.5,X_test,Y_test)
print(μ)
```

```
old [41921.]
new [3.04930416e+12]
[48808.49183588]
1
[5.13094674e+08]
2
[2.69698044e+12]
3
[7.08672347e+15]
4
[9.30717481e+18]
5
[6.10702152e+21]
6
[2.00054654e+24]
7
[3.26670626e+26]
8
[2.65078007e+28]
9
[1.06223842e+30]
10
[2.0752247e+31]
11
[1.92335314e+32]
12
[7.95130359e+32]
13
[1.2460027e+33]
14
6.7138671875e-08
```

In [123…
```
plt.plot(fold__min_fnew_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('Absolute Difference in Loss')
plt.title ('Absolute Difference in Loss VS Iterations')
plt.show()
```



In [124…
```
plt.plot(rmse_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('RMSE')
plt.title ('RMSE VS Iterations')
plt.show()
```

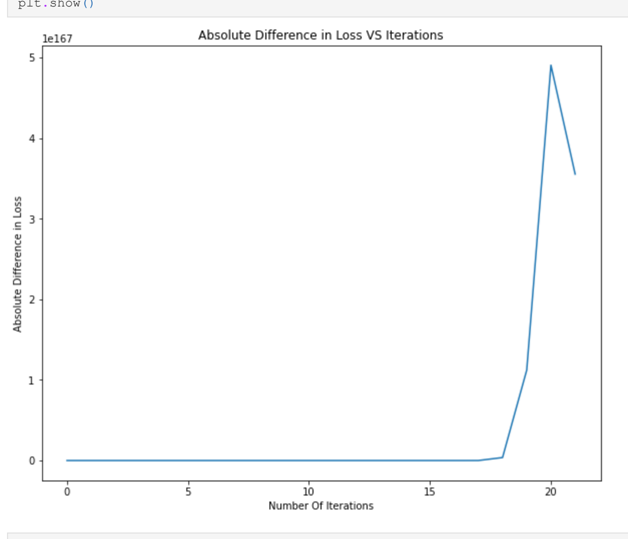


Air Travel Dataset

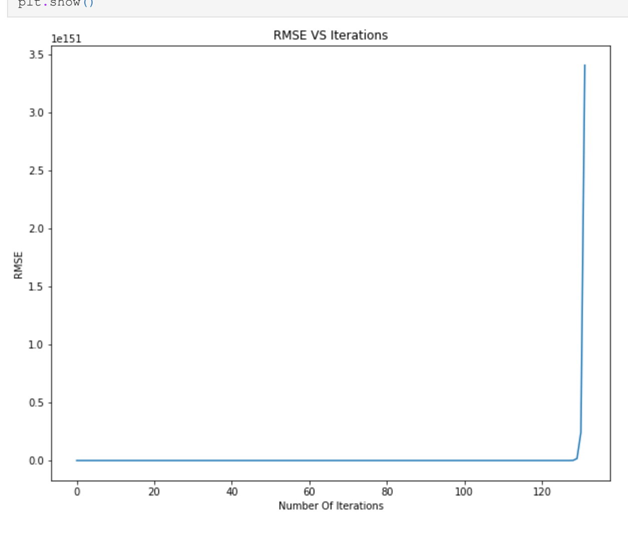
In [101…
```
X_train = adf_train.loc[:, adf_train.columns != 'price']
Y_train = adf_train[['price']]

X_test = (adf_train.loc[:, adf_train.columns != 'price']).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))
X_test = np.append(bias_column,X_test,axis=1)
Y_test = (adf_train[['price']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))
fold__min_fnew_List,rmse_List,μ= stepLengthBolddriver(X,Y,B,0.001,1.1,0.5,X_test,Y_test)
```

```
old [18271457.6459]
new [1.74157925e+20]
[4.66289206e+08]
1
[1.60417376e+15]
2
[2.76407279e+21]
3
[2.3816278e+27]
4
[1.02605863e+33]
5
[2.21024187e+38]
6
[2.38053975e+43]
7
[1.2819676e+48]
8
[3.45176005e+52]
9
[4.64684325e+56]
10
[3.12761431e+60]
11
[1.05238302e+64]
12
[1.77000866e+67]
13
[1.48760853e+70]
14
[6.2438849e+72]
15
[1.30723955e+75]
16
[1.36190289e+77]
17
[7.02616499e+78]
18
[1.77729629e+80]
19
[2.1590059e+81]
20
[1.20339731e+82]
21
[2.75207886e+82]
22
```

In [102…
```
plt.plot(fold__min_fnew_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('Absolute Difference in Loss')
plt.title ('Absolute Difference in Loss VS Iterations')
plt.show()
```



In [103…
```
plt.plot(rmse)
plt.xlabel('Number Of Iterations')
plt.ylabel('RMSE')
plt.title ('RMSE VS Iterations')
plt.show()
```

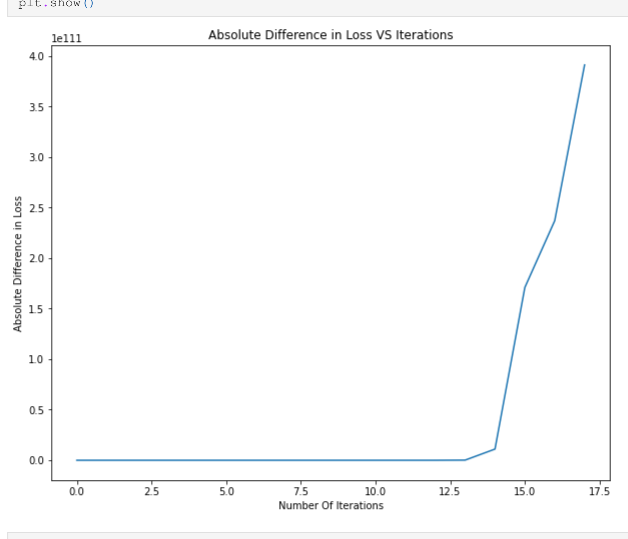


Parkinsons Dataset

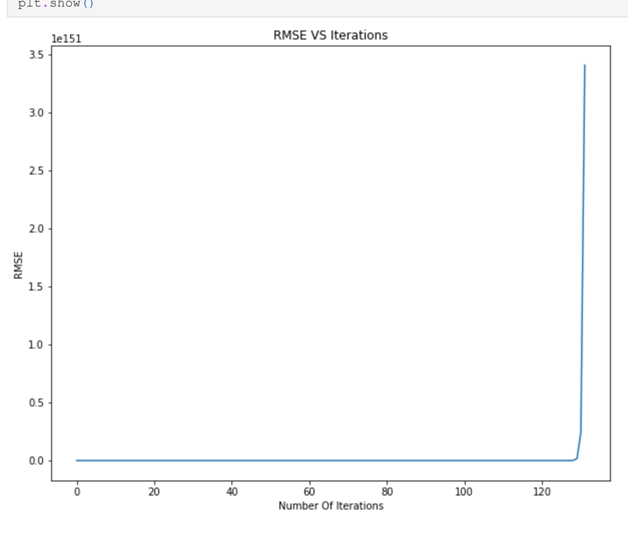
In [104…
```
X_train = pdf_train.loc[:, pdf_train.columns != 'total_UPDRS']
Y_train = pdf_train[['total_UPDRS']]

X_test = (pdf_train.loc[:, pdf_train.columns != 'total_UPDRS']).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))
X_test = np.append(bias_column,X_test,axis=1)
Y_test = (pdf_train[['total_UPDRS']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))
fold__min_fnew_List,rmse_List,μ= stepLengthBolddriver(X,Y,B,0.001,1.1,0.5,X_test,Y_test)
```

```
old [3893459.50415063]
new [8.38820951e+16]
[4224151.72379144]
1
[6.96562241e+11]
2
[5.74477782e+16]
3
[2.3689275e+21]
4
[4.8841588e+25]
5
[5.03473622e+29]
6
[2.59472621e+33]
7
[6.68485643e+36]
8
[8.60783689e+39]
9
[5.53768915e+42]
10
[1.77851497e+45]
11
[2.84709611e+47]
12
[2.26461974e+49]
13
[8.89331878e+50]
14
[1.70176739e+52]
15
[1.54310709e+53]
16
[6.22464199e+53]
17
[9.44227364e+53]
18
```

In [105…
```
plt.plot(fold__min_fnew_List)
plt.xlabel('Number Of Iterations')
plt.ylabel('Absolute Difference in Loss')
plt.title ('Absolute Difference in Loss VS Iterations')
plt.show()
```



In [106…
```
plt.plot(rmse)
plt.xlabel('Number Of Iterations')
plt.ylabel('RMSE')
plt.title ('RMSE VS Iterations')
plt.show()
```



3. Look-ahead optimizer

In [ ]:
```
def lookAheadOptimizer(X,Y,B_old,p,k,a,xtest,ytest):
    μ =μ_old *μ_plus
    B_new = B_old -(μ* lossGrad(X,Y,B_old))
    i= 0
    fold__min_fnew_List = []
    rmse_List = []
    numberOfIterations =500
    for t in range (500):

    while(loss(X,Y,B_old) - (loss(X,Y,B_new)) <= 0):
        B_new = B_old -(μ* lossGrad(X,Y,B_old))
        fold__min_fnew_List.append(abs(loss(X,Y,B_old)-loss(X,Y,B_new)))
        print(RMSE(xtest,ytest,B_old))
        rmse_List.append(RMSE(xtest,ytest,B_old)[0])
        B_old = B_new
        i += 1
        μ = μ*μ_minus
    print (i)
    return fold__min_fnew_List,rmse_List,μ
```

In [ ]:

In [ ]:

In [ ]:

In [ ]: