Lab Machine Learning

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Exercise 3

Exercise 1: Gradient Descent on Rosenbrock function

In [1]:
```
from mpl_toolkits import mplot3d
```

In [2]:
```
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
```

Parameters:-

In [3]:
```
a = 1
b = 100
```

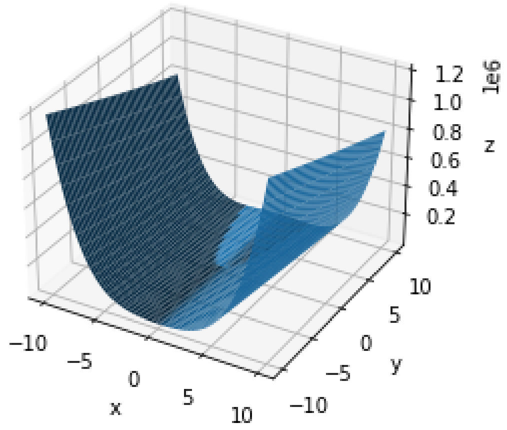
Rosenbrock Function

In [4]:
```
def func(x, y):
    return (a - x)**2 + b*((y - x**2)**2)
```

3D Plot of the Rosenbrock Function

In [5]:
```
x = np.linspace(-10, 10, 50)
y = np.linspace(-10, 10, 50)
X, Y = np.meshgrid(x, y)
Z = func(X, Y)
fig = plt.figure()
ax = plt.axes(projection='3d')
ax.plot_surface(X, Y, Z)
ax.set_xlabel('x')
ax.set_ylabel('y')
ax.set_zlabel('z')
```

Out[5]:
```
Text(0.5, 0, 'z')
```



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

Partial gradient:

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

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

In [24]:

```
def grad(x, y):
    f_x = 2*(x-a) - 4*b*x*(y - x**2)
    f_y = 2*b*(y - x**2)
    return f_x, f_y
```

Optimizing the function with Gradient Descent. Here we will use different values of the step length alpha by hit and trial to minimize this function.

In [27]:

```
def grad_descent(x, y, alpha, n_iter):
    l = np.zeros((n_iter,2))
    for i in range(n_iter):
        x_n = x - alpha*(grad(x, y)[0])
        y_n = y - alpha*(grad(x, y)[1])
        x, y = x_n, y_n
        l[i] = [x,y]
    return l
```

In [28]:

```
l = grad_descent(3, 7, 10**(-5), 10000000)
l
```

Out[28]:

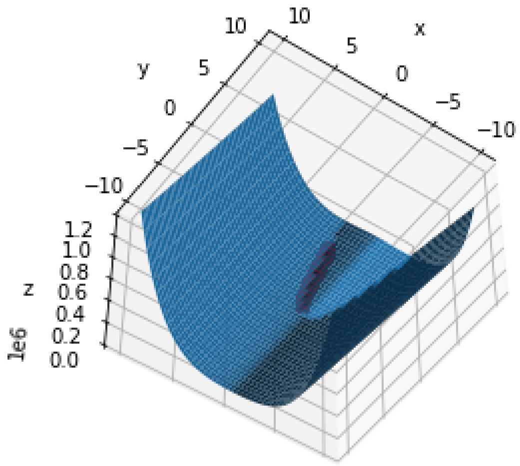
```
array([[2.97596   , 7.004     ],
       [2.95387055, 7.00770468],
       [2.93353665, 7.01113997],
       ...,
       [1.        , 1.        ],
       [1.        , 1.        ],
       [1.        , 1.        ]])
```

In [29]:

```
x = np.linspace(-10, 10, 50)
y = np.linspace(-10, 10, 50)
X, Y = np.meshgrid(x, y)
Z = func(X, Y)

xx = l[:,0]
```

```
yy = l[:,1]
zz = func(xx,yy)

fig = plt.figure()
ax = plt.axes(projection='3d')
ax.plot_surface(X, Y, Z)
ax.view_init(elev=-50., azim=55.)
ax.plot(xx, yy, 'ro', alpha=0.5) # note the 'ro' (no '-') and the alpha

ax.set_xlabel('x')
ax.set_ylabel('y')
ax.set_zlabel('z')
```

Out[29]: Text(0.5, 0, 'z')



Exercise 2: Linear Regression with Gradient Descent

Part A: (Datasets)

In [11]:
```
import pandas as pd
```

In [13]:
```
file = open("airq402.txt", 'r')
file.read()
```

Out[13]:
```
'Dataset:   airq402.dat\n\nSource: U.S. Department of Transportation\n\nDescription:
Airfsres and passengers for U.S. Domestic Routes\nfor 4th Quarter of 2002.\n\nVariab
les/Columns\n\nCity1   1-3\nCity2   5-7\nAverage Fare    11-17\nDistance      20-23
\nAverage weekly passengers   26-33\nmarket leading airline    36-37\nmarket share
40-45\nAverage fare     48-54\nLow price airline    57-58\nmarket share    61-66\npric
e     69-75'
```

Reading the three Data Files using Pandas

In [30]:
```
wine_quality = pd.read_csv("winequality-red.csv",sep=";")
airfare_pr = pd.read_fwf("airq402.data", header=None, names=["City1", "City2", "Aver
parkisons = pd.read_csv("parkinsons_updrs.data", sep=",")
```

This is how the dataframes look:

In [5]:

```
wine_quality
```

Out[5]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcoho
0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4
1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	0.68	9.8
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	0.65	9.8
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	0.58	9.8
4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4
...	...	...	...	...	...	...	...	...	...	...	..
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10.5
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11.2
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	11.0
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10.2
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11.0

1599 rows × 12 columns

In [31]:

```
airfare_pr
```

Out[31]:

	City1	City2	Average Fare1	Distance	Average weekly passengers	market leading airline	market share1	Average fare2	Low price airline	market share2	pric
0	CAK	ATL	114.47	528	424.56	FL	70.19	111.03	FL	70.19	111.0
1	CAK	MCO	122.47	860	276.84	FL	75.10	123.09	DL	17.23	118.9
2	ALB	ATL	214.42	852	215.76	DL	78.89	223.98	CO	2.77	167.1
3	ALB	BWI	69.40	288	606.84	WN	96.97	68.86	WN	96.97	68.8
4	ALB	ORD	158.13	723	313.04	UA	39.79	161.36	WN	15.34	145.4
...	...	...	...	...	...	...	...	...	...	...	.
995	SYR	TPA	136.16	1104	184.34	US	33.37	135.82	DL	28.65	118.5
996	TLH	TPA	83.28	200	232.71	FL	99.57	82.55	FL	99.57	82.5
997	TPA	IAD	159.97	814	843.80	US	46.19	159.65	DL	13.89	159.0
998	TPA	PBI	73.57	174	214.45	WN	99.74	73.44	WN	99.74	73.4
999	IAD	PBI	126.67	859	475.65	US	56.28	129.92	DL	38.57	121.9

1000 rows × 11 columns

Converting Non-numeric values in the columns City, Market leading airline and Low Price airline to numerical values using Pandas get_dummies.

In [32]:
```
airfare_price = pd.get_dummies(airfare_pr)
airfare_price
```

Out[32]:

	Average Fare1	Distance	Average weekly passengers	market share1	Average fare2	market share2	price	City1_ABQ	City1_ACY	City1
0	114.47	528	424.56	70.19	111.03	70.19	111.03	0	0	
1	122.47	860	276.84	75.10	123.09	17.23	118.94	0	0	
2	214.42	852	215.76	78.89	223.98	2.77	167.12	0	0	
3	69.40	288	606.84	96.97	68.86	96.97	68.86	0	0	
4	158.13	723	313.04	39.79	161.36	15.34	145.42	0	0	
...	...	...	...	...	...	...	...	...	...	
995	136.16	1104	184.34	33.37	135.82	28.65	118.51	0	0	
996	83.28	200	232.71	99.57	82.55	99.57	82.55	0	0	
997	159.97	814	843.80	46.19	159.65	13.89	159.02	0	0	
998	73.57	174	214.45	99.74	73.44	99.74	73.44	0	0	
999	126.67	859	475.65	56.28	129.92	38.57	121.94	0	0	

1000 rows × 217 columns

In [39]:
```
parkisons
```

Out[39]:

	subject#	age	sex	test_time	motor_UPDRS	total_UPDRS	Jitter(%)	Jitter(Abs)	Jitter:RAP
0	1	72	0	5.6431	28.199	34.398	0.00662	0.000034	0.00401
1	1	72	0	12.6660	28.447	34.894	0.00300	0.000017	0.00132
2	1	72	0	19.6810	28.695	35.389	0.00481	0.000025	0.00205
3	1	72	0	25.6470	28.905	35.810	0.00528	0.000027	0.00191
4	1	72	0	33.6420	29.187	36.375	0.00335	0.000020	0.00093
...	...	...	...	...	...	...	...	...	...
5870	42	61	0	142.7900	22.485	33.485	0.00406	0.000031	0.00167
5871	42	61	0	149.8400	21.988	32.988	0.00297	0.000025	0.00119
5872	42	61	0	156.8200	21.495	32.495	0.00349	0.000025	0.00152
5873	42	61	0	163.7300	21.007	32.007	0.00281	0.000020	0.00128
5874	42	61	0	170.7300	20.513	31.513	0.00282	0.000021	0.00135

5875 rows × 22 columns

Checking out if any of the rows have missing or null values.

In [37]:
```
Wq_null = wine_quality.isnull()
if_row_null_Wq = Wq_null.any(axis = 1)
```

```
row_null_Wq = wine_quality[if_row_null_Wq]
row_null_Wq
```

Out[37]:

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

In [38]:

```
Ap_null = airfare_price.isnull()
if_row_null_Ap = Ap_null.any(axis = 1)
row_null_Ap = airfare_price[if_row_null_Ap]
row_null_Ap
```

Out[38]:

Average Fare1	Distance	Average weekly passengers	market share1	Average fare2	market share2	price	City1_ABQ	City1_ACY	City1_ALE

0 rows × 217 columns

In [40]:

```
p_null = parkisons.isnull()
if_row_null_p = p_null.any(axis = 1)
row_null_p = parkisons[if_row_null_p]
row_null_p
```

Out[40]:

subject#	age	sex	test_time	motor_UPDRS	total_UPDRS	Jitter(%)	Jitter(Abs)	Jitter:RAP	Jitter

0 rows × 22 columns

None of the dataframes above has zero or null rows. So there is no row that we can remove.

Splitting the dataset into 80% training data and 20% test data.

In [41]:

```
def split(file):
    r, c = np.shape(file)
    size = int(0.8*r)
    train = file.iloc[0:size]
    test = file.iloc[size :]
    return train, test
```

If there any columns that can be removed.

In [94]:

```
winequality_corr = wine_quality.corr(method = 'pearson')
winequality_corr
```

Out[94]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	
fixed acidity	1.000000	-0.256131	0.671703	0.114777	0.093705	-0.153794	-0.113181	0.668047	-0.6
volatile acidity	-0.256131	1.000000	-0.552496	0.001918	0.061298	-0.010504	0.076470	0.022026	0.2

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	
citric acid	0.671703	-0.552496	1.000000	0.143577	0.203823	-0.060978	0.035533	0.364947	-0.5
residual sugar	0.114777	0.001918	0.143577	1.000000	0.055610	0.187049	0.203028	0.355283	-0.0
chlorides	0.093705	0.061298	0.203823	0.055610	1.000000	0.005562	0.047400	0.200632	-0.2
free sulfur dioxide	-0.153794	-0.010504	-0.060978	0.187049	0.005562	1.000000	0.667666	-0.021946	0.0
total sulfur dioxide	-0.113181	0.076470	0.035533	0.203028	0.047400	0.667666	1.000000	0.071269	-0.0
density	0.668047	0.022026	0.364947	0.355283	0.200632	-0.021946	0.071269	1.000000	-0.3
pH	-0.682978	0.234937	-0.541904	-0.085652	-0.265026	0.070377	-0.066495	-0.341699	1.0
sulphates	0.183006	-0.260987	0.312770	0.005527	0.371260	0.051658	0.042947	0.148506	-0.1
alcohol	-0.061668	-0.202288	0.109903	0.042075	-0.221141	-0.069408	-0.205654	-0.496180	0.2
quality	0.124052	-0.390558	0.226373	0.013732	-0.128907	-0.050656	-0.185100	-0.174919	-0.0

In [95]:

```
airfare_corr = airfare_price.corr(method = 'pearson')
airfare_corr
```

Out[95]:

	Average Fare1	Distance	Average weekly passengers	market share1	Average fare2	market share2	price	City1_ABQ
Average Fare1	1.000000	0.587169	-0.126175	-0.234142	0.981462	-0.458660	0.866410	-0.015512
Distance	0.587169	1.000000	-0.090131	-0.531406	0.564082	-0.367831	0.583239	-0.019194
Average weekly passengers	-0.126175	-0.090131	1.000000	-0.067605	-0.100946	0.034241	-0.142314	-0.046326
market share1	-0.234142	-0.531406	-0.067605	1.000000	-0.220801	0.306832	-0.307672	0.039731
Average fare2	0.981462	0.564082	-0.100946	-0.220801	1.000000	-0.472838	0.826511	-0.019783
...	...	...	...	...	...	...	...	...
Low price airline_TZ	0.032484	0.042391	0.225821	-0.135279	0.052165	-0.085219	-0.057155	-0.025400
Low price airline_UA	0.157407	0.016713	-0.088678	0.070145	0.159428	-0.120865	0.108960	-0.032662
Low price airline_US	0.135060	-0.027004	-0.067905	0.056783	0.119931	-0.054411	0.083681	-0.045380
Low price airline_WN	-0.383648	-0.218735	0.020247	0.140842	-0.377977	0.407897	-0.319557	0.068990

	Average Fare1	Distance	Average weekly passengers	market share1	Average fare2	market share2	price	City1_ABQ
Low price airline_YX	0.019288	-0.014731	-0.018707	-0.010773	0.016795	0.044103	0.049538	-0.007427

217 rows × 217 columns

In [96]:

```
parkisons_corr = parkisons.corr(method = 'pearson')
parkisons_corr
```

Out[96]:

	subject#	age	sex	test_time	motor_UPDRS	total_UPDRS	Jitter(%)
subject#	1.000000	-0.030864	0.286851	-0.000882	0.252919	0.253643	0.135448
age	-0.030864	1.000000	-0.041602	0.019884	0.273665	0.310290	0.023071
sex	0.286851	-0.041602	1.000000	-0.009805	-0.031205	-0.096559	0.051422
test_time	-0.000882	0.019884	-0.009805	1.000000	0.067918	0.075263	-0.022837
motor_UPDRS	0.252919	0.273665	-0.031205	0.067918	1.000000	0.947231	0.084816
total_UPDRS	0.253643	0.310290	-0.096559	0.075263	0.947231	1.000000	0.074247
Jitter(%)	0.135448	0.023071	0.051422	-0.022837	0.084816	0.074247	1.000000
Jitter(Abs)	0.075156	0.035691	-0.154645	-0.011365	0.050903	0.066927	0.865577
Jitter:RAP	0.120339	0.010255	0.076718	-0.028888	0.072684	0.064015	0.984181
Jitter:PPQ5	0.136474	0.013199	0.087995	-0.023290	0.076291	0.063352	0.968214
Jitter:DDP	0.120350	0.010258	0.076703	-0.028876	0.072698	0.064027	0.984184
Shimmer	0.146202	0.101554	0.058736	-0.033870	0.102349	0.092141	0.709791
Shimmer(dB)	0.142864	0.111130	0.056481	-0.030962	0.110076	0.098790	0.716704
Shimmer:APQ3	0.112950	0.098912	0.044937	-0.029020	0.084261	0.079363	0.664149
Shimmer:APQ5	0.138264	0.089983	0.064819	-0.036504	0.092105	0.083467	0.694002
Shimmer:APQ11	0.173333	0.135238	0.023360	-0.039110	0.136560	0.120838	0.645965
Shimmer:DDA	0.112949	0.098913	0.044938	-0.029017	0.084260	0.079363	0.664147
NHR	0.168743	0.007093	0.168170	-0.026357	0.074967	0.060952	0.825294
HNR	-0.206929	-0.104842	-0.000167	0.036545	-0.157029	-0.162117	-0.675188
RPDE	0.147300	0.090208	-0.159262	-0.038887	0.128607	0.156897	0.427128
DFA	0.097464	-0.092870	-0.165113	0.019261	-0.116242	-0.113475	0.226550
PPE	0.157559	0.120790	-0.099901	-0.000563	0.162433	0.156195	0.721849

22 rows × 22 columns

In the above three datasets if the correlation between the columns of the dataframe with the target vector column have values between -0.3 and +0.3, then the columns are weakly correlated with the target column and hence can also be removed as they do not significantly contribute to the target,

Part B: Linear Regression with Real-World Data

Loss function

In [42]:
```
def loss(X, Y, beta):
    m, n = np.shape(X)
    sum = 0
    for i in range(m):
        sum += (Y[i] - np.dot(X[i], beta))**2
    return sum
```

Gradient of the Loss Function

In [43]:
```
def grad_loss(X, Y, beta):
    m, n = np.shape(X)
    grad = np.zeros(n)
    for k in range(n):
        s = 0
        for i in range(m):
            s += (-2)*(Y[i] - np.dot(X[i], beta))*X[i][k]
        grad[k] = s
    return grad
```

Gradient Descent function

In [44]:
```
def grad_descent(X, Y, x_t, y_t, beta, alpha, i_max):
    n= np.size(beta)
    m = np.size(y_t)
    diff = np.zeros(i_max)
    Rmse = np.zeros(i_max)
    beta_n = np.zeros(n)
    for i in range(i_max):
        sum = 0
        for j in range(n):
            beta_n[j] = beta[j] - (alpha*(grad_loss(X, Y, beta)[j]))
        diff[i] = abs(loss(X, Y, beta) - loss(X, Y, beta_n))
        for k in range(m):
            sum += (np.dot(x_t[k], beta_n) - y_t[k])**2
        Rmse[i] = np.sqrt(sum/m)
        beta = np.array(beta_n)
    return beta_n, diff, Rmse
```

Extracting X^{train}, Y^{train}, X^{test} and Y^{test} from our dataframes

In [45]:
```
def Extract(f, col_name):
    train, test = split(f)
    r, c = np.shape(train)
    x_train = train.loc[:, train.columns != col_name]
    x_train = x_train.to_numpy()
    bias_column1 = np.ones(shape=(r,1))
    X_train = np.append(bias_column1,x_train,axis=1)
    y_train = train.loc[:, train.columns == col_name]
    Y_train = y_train.to_numpy()
```

```
    k, l = np.shape(test)
    x_test = test.loc[:, test.columns != col_name]
    x_test = x_test.to_numpy()
    bias_column2 = np.ones(shape=(k,1))
    X_test = np.append(bias_column2,x_test,axis=1)
    y_test = test.loc[:, test.columns == col_name]
    Y_test = y_test.to_numpy()
    return X_train, Y_train, X_test, Y_test
```

Linear Regression using Gradient descent For the Wine_quality dataframe

Putting the dataframe in the Extract function above to get training and test datasets.

In [46]:
```
Wq_train_features, Wq_train_target, Wq_test_features, Wq_test_target = Extract(wine_
```

Choice for alpha $10^{-5}, 10^{-7}$ and 10^{-9}

By hit and trial, the best value found for alpha is as given below:

In [52]:
```
alpha1 = 10**(-7)
Wq_rows, Wq_col = np.shape(Wq_train_features)
beta_Wq = np.zeros(Wq_col)
beta_pred_Wq, abs_difference_Wq, RMSE_Wq = grad_descent(Wq_train_features, Wq_train_
```

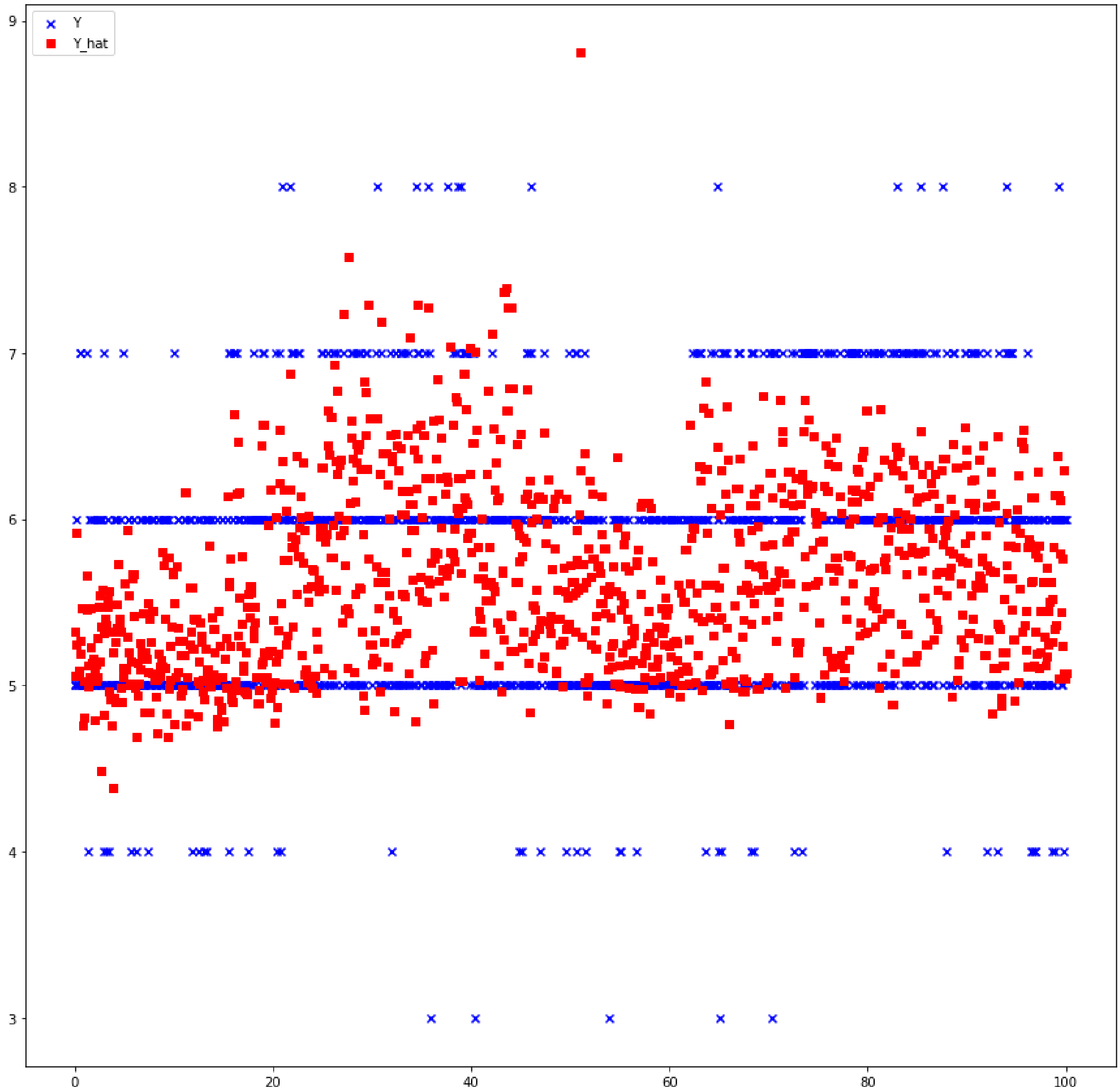
After performing the iterations for 500 times we get the following value for beta.

In [53]:
```
beta_pred_Wq
```

Out[53]:
```
array([ 0.02891247,  0.20781084,  0.01143929,  0.00645014,  0.04829093,
        0.00225899,  0.01137366, -0.00332255,  0.02876486,  0.09743182,
        0.02084436,  0.31882271])
```

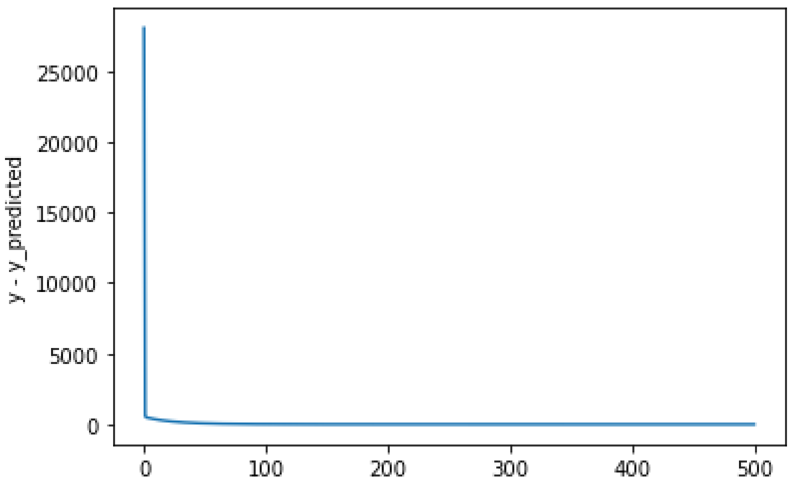
Plotting the predicted target vector and actual target vector shows that in the prediction vector more values are clustered around the points of the target vector which occurs most often.

In [54]:
```
Wq_train_target_pred = np.dot(Wq_train_features, beta_pred_Wq)
Wq_train_target_ = np.reshape(Wq_train_target, np.shape(Wq_train_target_pred))
fig = plt.figure(figsize=(15,15))
axis = np.linspace(0, 100, 1279)
ax = fig.add_subplot(111)
ax.scatter(axis, Wq_train_target_, c='b', marker='x', label='Y')
ax.scatter(axis, Wq_train_target_pred, c='r', marker='s', label='Y_hat')
ax.legend(loc='upper left')
plt.show()
```



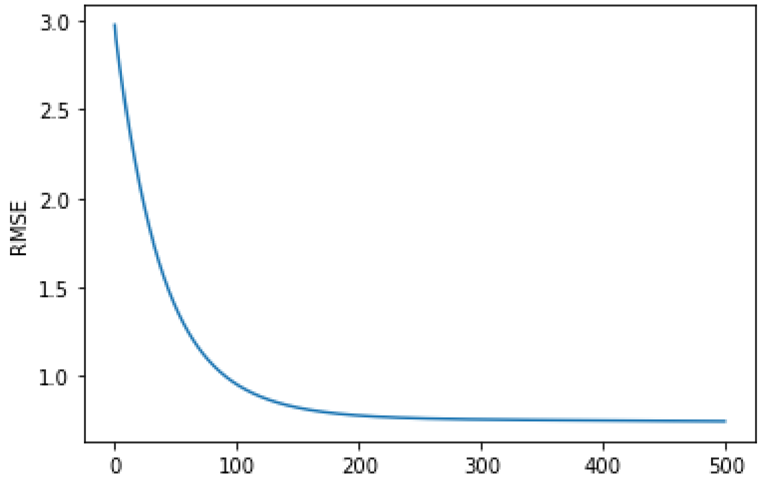
With each iteration, the absolute difference between the values of loss function at previous and present calculated values of beta is decreasing. Hence beta is getting better after each iteration.

In [55]:
```
abs_Wq = abs_difference_Wq
plt.plot(abs_Wq)
plt.ylabel('y - y_predicted')
plt.show()
```



With each iteration, the root mean square error of the loss function at previous and present calculated values of beta is decreasing. Hence beta is getting better after each iteration.

In [56]:
```
Wq_y = RMSE_Wq
plt.plot(Wq_y)
plt.ylabel('RMSE')
plt.show()
```



Linear Regression using Gradient descent For the airfare_Price dataframe

While submitting the file Airfare dataframe was taking too much time so couldn't run. Otherwise the code is fine.

Putting the dataframe in the Extract function above to get training and test datasets.

In [57]:
```
Ap_train_features, Ap_train_target, Ap_test_features, Ap_test_target = Extract(airfa
```

By hit and trial, the best value found for alpha is as given below:

In [97]:
```
alpha2 = 10**(-9)
Ap_rows, Ap_col = np.shape(Ap_train_features)
beta_Ap = np.zeros(Ap_col)
beta_pred_Ap, abs_difference_Ap, RMSE_Ap = grad_descent(Ap_train_features, Ap_train_
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
~\AppData\Local\Temp/ipykernel_15588/943760448.py in <module>
      2 Ap_rows, Ap_col = np.shape(Ap_train_features)
      3 beta_Ap = np.zeros(Ap_col)
----> 4 beta_pred_Ap, abs_difference_Ap, RMSE_Ap = grad_descent(Ap_train_features, A
p_train_target, Ap_test_features, Ap_test_target, beta_Ap, alpha2, 100)

~\AppData\Local\Temp/ipykernel_15588/3595345261.py in grad_descent(X, Y, x_t, y_t, b
eta, alpha, i_max)
      8         sum = 0
      9         for j in range(n):
---> 10             beta_n[j] = beta[j] - (alpha*(grad_loss(X, Y, beta)[j]))
     11         diff[i] = abs(loss(X, Y, beta) - loss(X, Y, beta_n))
```

```
        for k in range(m):

~\AppData\Local\Temp/ipykernel_15588/3859566424.py in grad_loss(X, Y, beta)
        s = 0
        for i in range(m):
---->       s += (-2)*(Y[i] - np.dot(X[i], beta))*X[i][k]
        grad[k] = s
    return grad

<__array_function__ internals> in dot(*args, **kwargs)

KeyboardInterrupt:
```

After performing the iterations for 100 times we get the following value for beta.

In [ ]:

```python
beta_pred_Ap
```

Plotting the predicted target vector and actual target vector shows that in the prediction vector more values are clustered around the points of the target vector which occurs most often.

In [ ]:

```python
Ap_train_target_pred = np.dot(Ap_train_features, beta_pred_Ap)
Ap_train_target_ = np.reshape(Ap_train_target, np.shape(Ap_train_target_pred))
fig = plt.figure(figsize=(15,15))
axis = np.linspace(0, 100, 800)
ax = fig.add_subplot(111)
ax.scatter(axis, Ap_train_target_, c='b', marker='x', label='Y')
ax.scatter(axis, Ap_train_target_pred, c='r', marker='s', label='Y_hat')
ax.legend(loc='upper left')
plt.show()
```

With each iteration, the absolute difference between the values of loss function at previous and present calculated values of beta is decreasing. Hence beta is getting better after each iteration.

In [ ]:

```python
abs_Ap = abs_difference_Ap
plt.plot(abs_Ap)
plt.ylabel('y - y_predicted')
plt.show()
```

With each iteration, the root mean square error of the loss function at previous and present calculated values of beta is decreasing. Hence beta is getting better after each iteration.

In [ ]:

```python
Ap_y = RMSE_Ap
plt.plot(ap_y)
plt.ylabel('RMSE')
plt.show()
```

Linear Regression using Gradient descent For the parkisons dataframe

Putting the dataframe in the Extract function above to get training and test datasets.

In [61]:

```python
p_train_features, p_train_target, p_test_features, p_test_target = Extract(parkisons
```

By hit and trial, the best value found for alpha is as given below:

In [69]:
```
alpha3 = 10**(-8)
p_rows, p_col = np.shape(p_train_features)
beta_p = np.zeros(p_col)
beta_pred_p, abs_difference_p, RMSE_p = grad_descent(p_train_features, p_train_targe
```

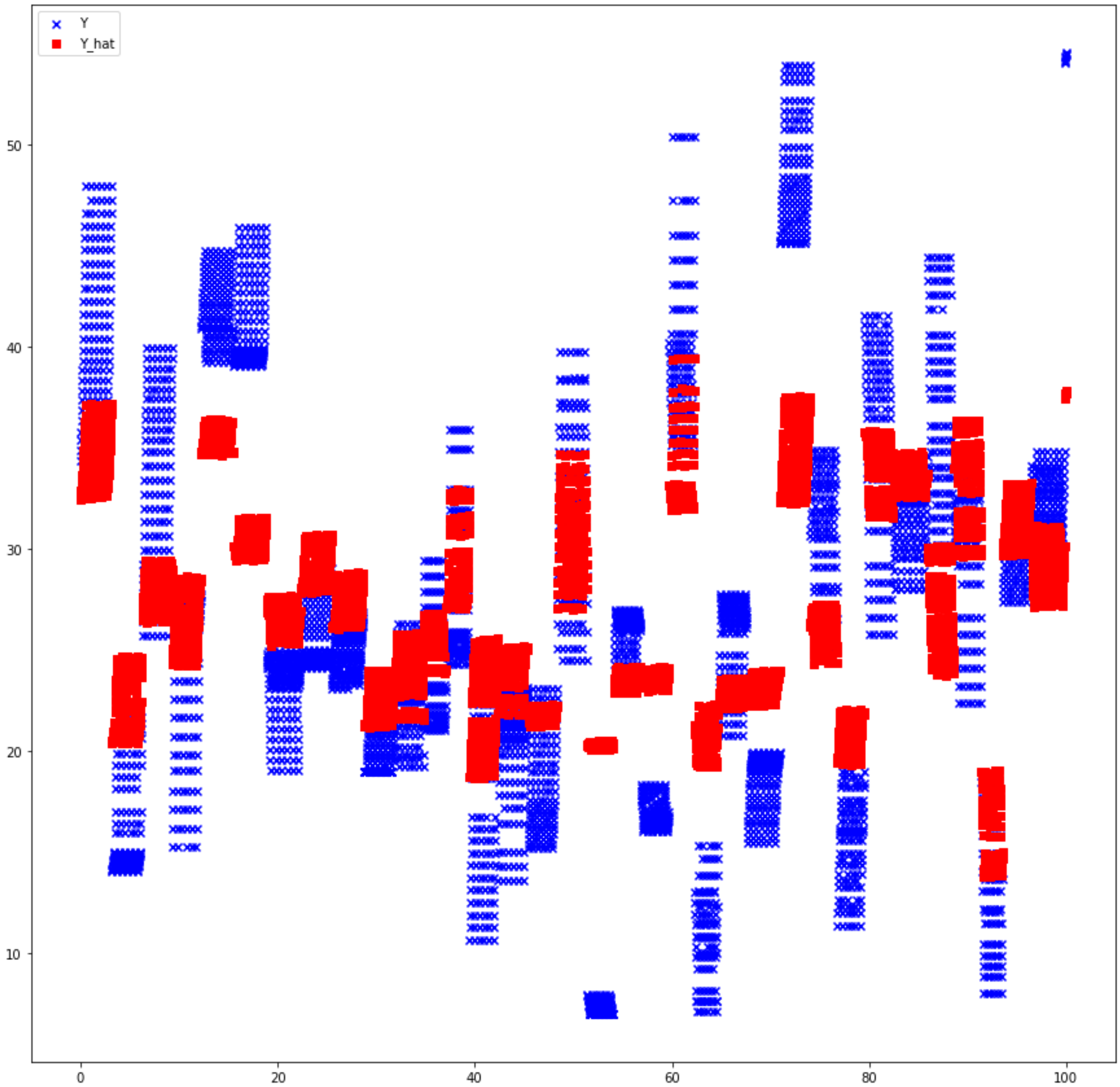
After performing the iterations for 100 times we get the following value for beta.

In [71]:
```
beta_pred_p
```

Out[71]:
```
array([ 2.88547579e-03,  4.02529123e-02,  2.47513651e-01, -5.42070036e-03,
        1.61993308e-03,  5.01109983e-01,  3.80098107e-05,  3.51025871e-07,
        1.97184808e-05,  1.93572367e-05,  5.91505059e-05,  1.69234130e-04,
        1.54753891e-03,  8.68010832e-05,  1.01451286e-04,  1.44391147e-04,
        2.60408346e-04,  2.20005322e-04,  1.97025700e-02,  3.24932075e-03,
        1.06304214e-03,  1.26914631e-03])
```

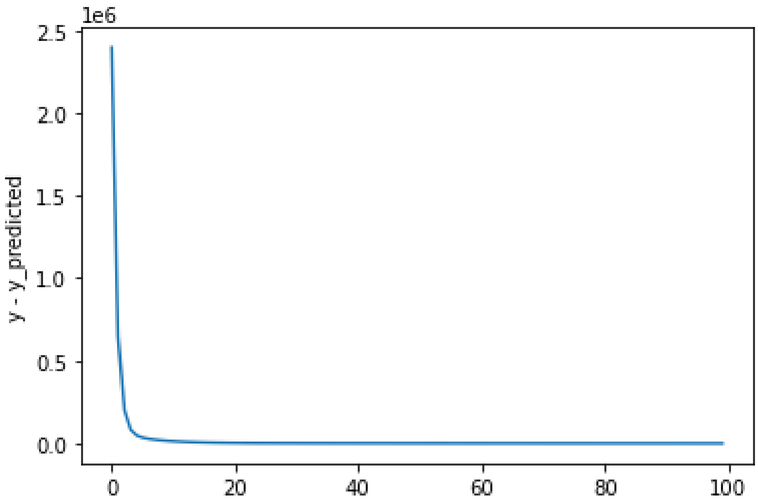
Plotting the predicted target vector and actual target vector shows that in the prediction vector more values are clustered around the points of the target vector which occurs most often.

In [72]:
```
p_train_target_pred = np.dot(p_train_features, beta_pred_p)
p_train_target_ = np.reshape(p_train_target, np.shape(p_train_target_pred))
fig = plt.figure(figsize=(15,15))
axis = np.linspace(0, 100, 4700)
ax = fig.add_subplot(111)
ax.scatter(axis, p_train_target_, c='b', marker='x', label='Y')
ax.scatter(axis, p_train_target_pred, c='r', marker='s', label='Y_hat')
ax.legend(loc='upper left')
plt.show()
```



With each iteration, the absolute difference between the values of loss function at previous and present calculated values of beta is decreasing. Hence beta is getting better after each iteration.

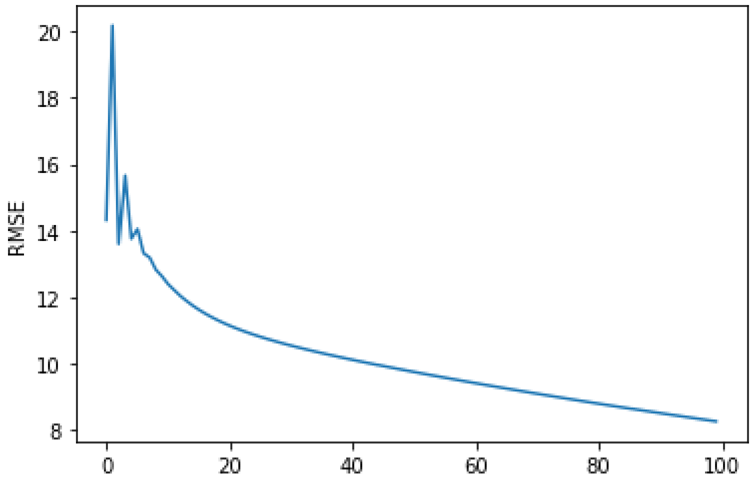
In [73]:
```
abs_p = abs_difference_p
plt.plot(abs_p)
plt.ylabel('y - y_predicted')
plt.show()
```



With each iteration, the root mean square error of the loss function at previous and present calculated values of beta is decreasing. Hence beta is getting better after each iteration.

In [74]:

```
p_y = RMSE_p
plt.plot(p_y)
plt.ylabel('RMSE')
plt.show()
```



Exercise 3: Steplength Control for Gradient Descent

Backtracking Line search

In [75]:

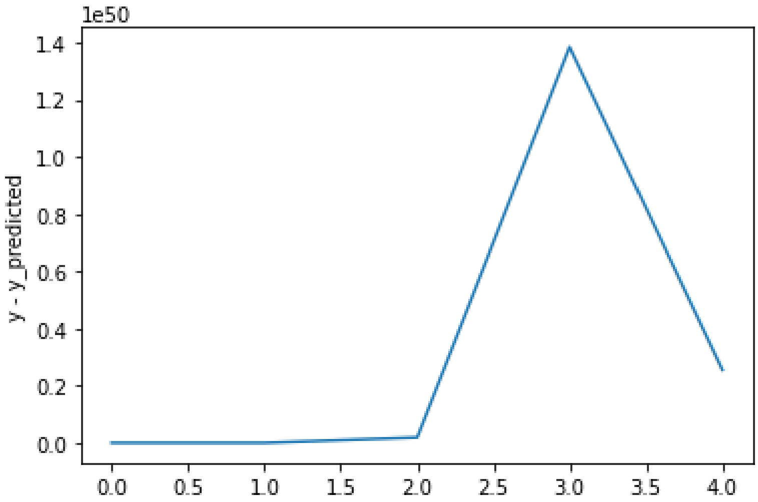
```
def backtracking(X, Y, x_t, y_t, beta, a, b):
    alpha = 1
    m, n = np.shape(X)
    m_t, n_t = np.shape(x_t)
    beta_new = np.zeros(n)
    diff = []
    Rmse = []
    for j in range(n):
        beta_new[j] = beta[j] - alpha*(grad_loss(X, Y, beta)[j])
    while loss(X, Y, beta_new) > (loss(X, Y, beta) - a*alpha*np.dot(grad_loss(X, Y,
        s = 0
        beta = np.array(beta_new)
        for j in range(n):
            beta_new[j] = beta[j] - alpha*(grad_loss(X, Y, beta)[j])
        diff.append(abs(loss(X, Y, beta) - loss(X, Y, beta_new)))
        for k in range(m_t):
            s += (np.dot(x_t[k], beta_new) - y_t[k])**2
        Rmse.append(np.sqrt(s/m))
        alpha = alpha*b
    return alpha, diff, Rmse
```

Backtracking to find alpha For the Wine_quality dataframe

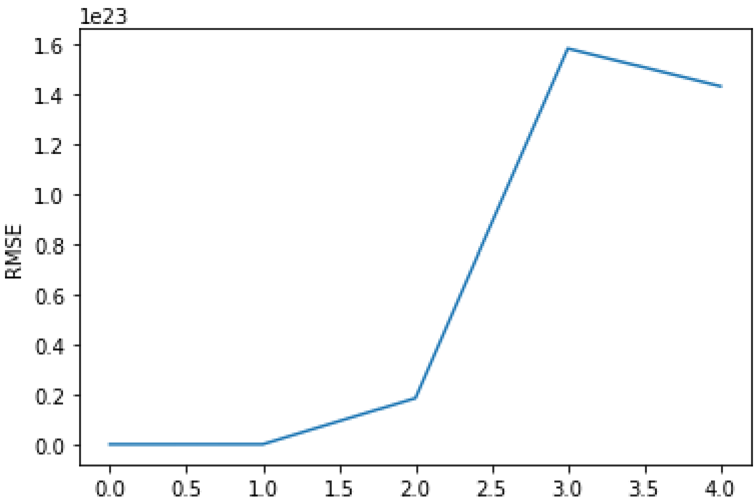
In [76]:
```
backtracking(Wq_train_features, Wq_train_target, Wq_test_features, Wq_test_target, b
```

Out[76]:
```
1.0000000000000002e-10
```

In [78]:
```
abs_dif_Wq = backtracking(Wq_train_features, Wq_train_target, Wq_test_features, Wq_t
plt.plot(abs_dif_Wq)
plt.ylabel('y - y_predicted')
plt.show()
```



In [79]:
```
rmse_Wq = backtracking(Wq_train_features, Wq_train_target, Wq_test_features, Wq_test
plt.plot(rmse_Wq)
plt.ylabel('RMSE')
plt.show()
```



Backtracking to find alpha For the airfare_price dataframe

In [80]:
```
backtracking(Ap_train_features, Ap_train_target, Ap_test_features, Ap_test_target, b
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
~\AppData\Local\Temp/ipykernel_15588/3198880513.py in <module>
----> 1 backtracking(Ap_train_features, Ap_train_target, Ap_test_features, Ap_test_t
arget, beta_Ap, 0.05, 0.001)[0]
```

```
~\AppData\Local\Temp/ipykernel_15588/2046868721.py in backtracking(X, Y, x_t, y_t, b
eta, a, b)
     12         beta = np.array(beta_new)
     13         for j in range(n):
---> 14             beta_new[j] = beta[j] - alpha*(grad_loss(X, Y, beta)[j])
     15         diff.append(abs(loss(X, Y, beta) - loss(X, Y, beta_new)))
     16         for k in range(m_t):

~\AppData\Local\Temp/ipykernel_15588/3859566424.py in grad_loss(X, Y, beta)
      5         s = 0
      6         for i in range(m):
----> 7             s += (-2)*(Y[i] - np.dot(X[i], beta))*X[i][k]
      8         grad[k] = s
      9     return grad

<__array_function__ internals> in dot(*args, **kwargs)

KeyboardInterrupt:
```

In [ ]:

```
abs_dif_Ap = backtracking(Ap_train_features, Ap_train_target, Ap_test_features, Ap_t
plt.plot(abs_dif_Ap)
plt.ylabel('y - y_predicted')
plt.show()
```

In [ ]:

```
rmse_Ap = backtracking(Ap_train_features, Ap_train_target, Ap_test_features, Ap_test
plt.plot(rmse_Ap)
plt.ylabel('RMSE')
plt.show()
```

Backtracking to find alpha For the parkisons dataframe

In [81]:

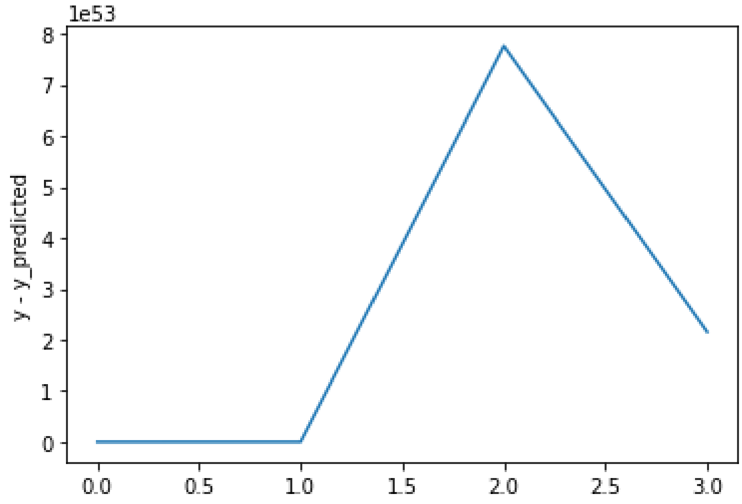
```
backtracking(p_train_features, p_train_target, p_test_features, p_test_target, beta_
```

Out[81]:

```
1.0000000000000002e-12
```

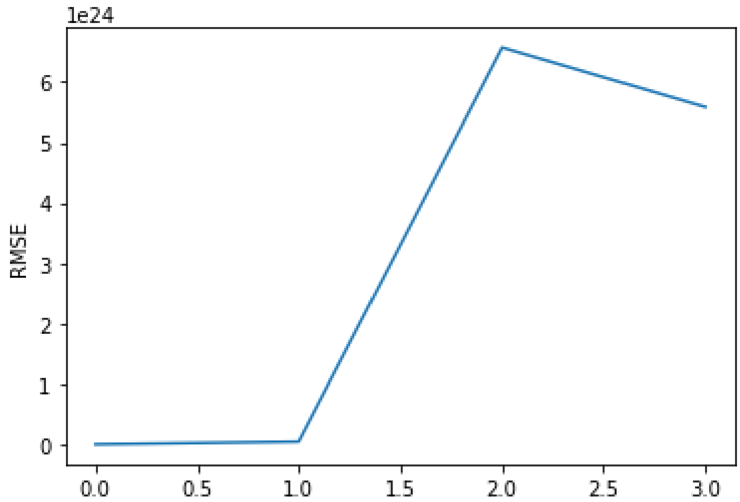
In [82]:

```
abs_dif_p = backtracking(p_train_features, p_train_target, p_test_features, p_test_t
plt.plot(abs_dif_p)
plt.ylabel('y - y_predicted')
plt.show()
```



In [83]:

```
rmse_p = backtracking(p_train_features, p_train_target, p_test_features, p_test_targ
plt.plot(rmse_p)
plt.ylabel('RMSE')
plt.show()
```



steplength-bolddriver

In [86]:

```
def boldDriver(X, Y, x_t, y_t, beta, alpha_old, a, b):
    alpha = alpha_old*a
    m, n = np.shape(X)
    m_t, n_t = np.shape(x_t)
    beta_new = np.zeros(n)
    diff = []
    Rmse = []
    for j in range(n):
        beta_new[j] = beta[j] - alpha*(grad_loss(X, Y, beta)[j])
    while loss(X, Y, beta) - loss(X, Y, beta_new) <= 0:
        s = 0
        beta = np.array(beta_new)
        for j in range(n):
            beta_new[j] = beta[j] - alpha*(grad_loss(X, Y, beta)[j])
        diff.append(abs(loss(X, Y, beta) - loss(X, Y, beta_new)))
        for k in range(m_t):
            s += (np.dot(x_t[k], beta_new) - y_t[k])**2
        Rmse.append(np.sqrt(s/m))
        alpha = alpha*b
    return alpha, diff, Rmse
```

BoldDriver to find alpha For the Wine_quality dataframe

In [87]:

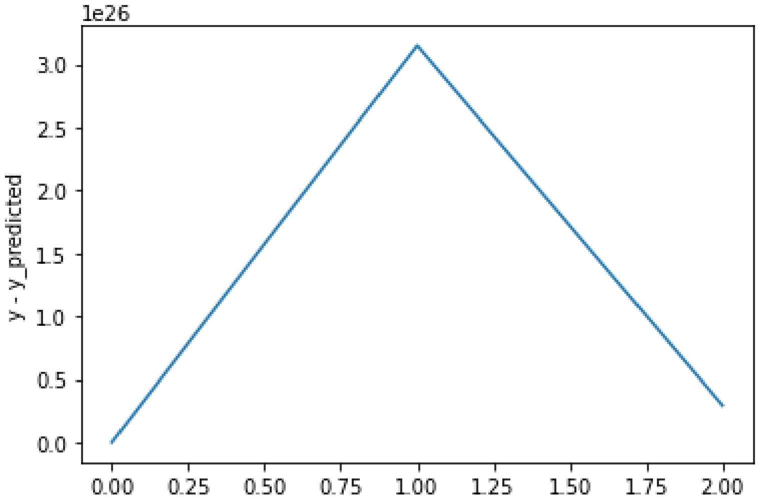
```
boldDriver(Wq_train_features, Wq_train_target, Wq_test_features, Wq_test_target, bet
```

Out[87]:

```
5.000000000000002e-12
```

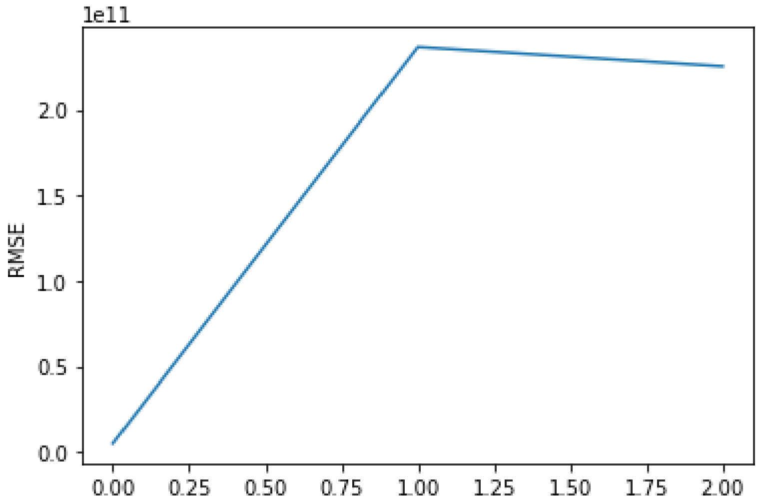
In [88]:

```
bd_diff_Wq = boldDriver(Wq_train_features, Wq_train_target, Wq_test_features, Wq_tes
plt.plot(bd_diff_Wq)
plt.ylabel('y - y_predicted')
plt.show()
```



In [89]:

```
bd_rmse_Wq = boldDriver(Wq_train_features, Wq_train_target, Wq_test_features, Wq_tes
plt.plot(bd_rmse_Wq)
plt.ylabel('RMSE')
plt.show()
```



BoldDriver to find alpha For the airfare_price dataframe

In [ ]:
```
boldDriver(Ap_train_features, Ap_train_target, Ap_test_features, Ap_test_target, bet
```

In [ ]:
```
abs_dif_Ap = boldDriver(Ap_train_features, Ap_train_target, Ap_test_features, Ap_tes
plt.plot(abs_dif_Ap)
plt.ylabel('y - y_predicted')
plt.show()
```

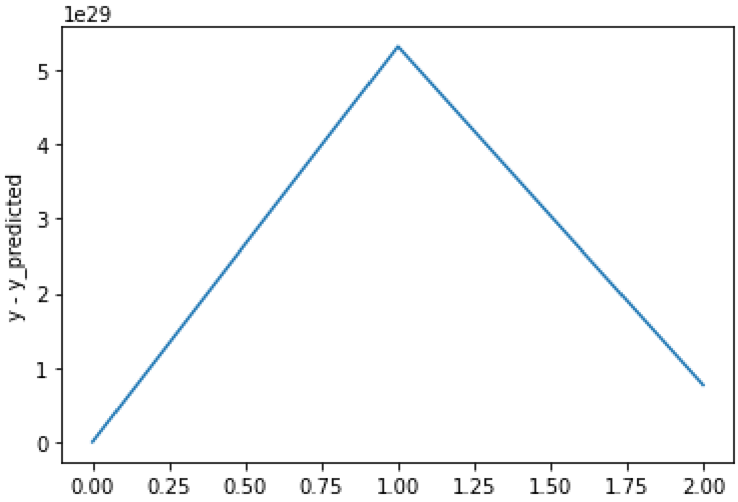
In [ ]:
```
rmse_Ap = boldDriver(Ap_train_features, Ap_train_target, Ap_test_features, Ap_test_t
plt.plot(zz)
plt.ylabel('RMSE')
plt.show()
```

BoldDriver to find alpha For the parkisons dataframe

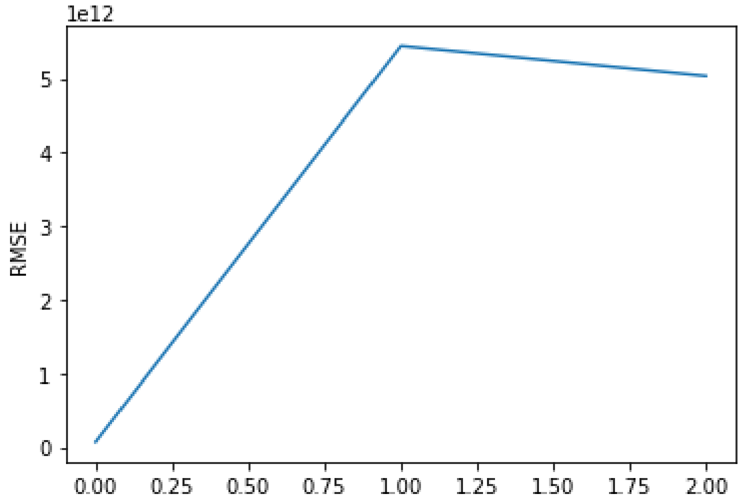
In [90]:
```
boldDriver(p_train_features, p_train_target, p_test_features, p_test_target, beta_p,
```

Out[90]:
```
5.000000000000001e-13
```

In [91]:
```
abs_dif_p = boldDriver(p_train_features, p_train_target, p_test_features, p_test_tar
plt.plot(abs_dif_p)
plt.ylabel('y - y_predicted')
plt.show()
```



In [92]:
```
rmse_p = boldDriver(p_train_features, p_train_target, p_test_features, p_test_target
plt.plot(rmse_p)
plt.ylabel('RMSE')
plt.show()
```



Look-ahead optimizer

In [ ]:

```
def lookahead(initial theta, loss func, k, slow weights phi step size alpha, gradien
    for outer loop:
        phi's are stored in theta
        for loop for k steps ahead:
            on minibatch d from data D
            new theta = old theta + gradient descent(loss func, old theta, d)
        new phi = old phi + alpha*(theta at the end of k iteration - old phi)

    return phi
```