ML Assignment 1

Linear Regression

5-fold Linear Regression for Abalone Dataset.

In [71]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import sklearn
import random
%matplotlib inline

dataset_location = 'abalone/Dataset.data/Dataset.data'
columns =(['sex','length','diameter','height','whole_weight','shucked_weight','viscera_
weight','shell_weight','rings'])
data = pd.read_csv(dataset_location,delim_whitespace=True,names=columns)
data = data.replace(to_replace ="M",value =2)
data = data.replace(to_replace ="F",value =1)
data = data.replace(to_replace ="I",value =0)
data = (data-data.min())/(data.max()-data.min())
data.head()
```

Out[71]:

	sex	length	diameter	height	whole_weight	shucked_weight	viscera_weight	shell_v
0	1.0	0.513514	0.521008	0.084071	0.181335	0.150303	0.132324	0.1
1	1.0	0.371622	0.352941	0.079646	0.079157	0.066241	0.063199	0.0
2	0.5	0.614865	0.613445	0.119469	0.239065	0.171822	0.185648	0.2
3	1.0	0.493243	0.521008	0.110619	0.182044	0.144250	0.149440	0.1
4	0.0	0.344595	0.336134	0.070796	0.071897	0.059516	0.051350	0.0

In [484]:

```
def plotFeatures(df,columns):
    plt.figure(figsize=(10, 14))
    for i in range(len(columns)):
        plt.subplot(7,2,i+1)
        plt.plot(df[columns[i]],df['rings'],marker='.',linestyle='none')
        plt.title("rings vs "+columns[i])
        plt.tight_layout()
# plotFeatures(data,columns[:-1])
```

In [73]:

```
def test_train_split(data,split=0.75):
    data_copy = data.copy()
    train = data_copy.sample(frac=split, random_state=0)
    test = data_copy.drop(train.index)
    train = train.sample(frac=1).reset_index(drop=True)
    test = test.sample(frac=1).reset_index(drop=True)
    return train, test

def cross_validation_split(data, folds=5):
    splits = np.array_split(data, folds)
    y_splits = np.array_split(data['rings'], folds)
    x_splits = np.array_split(data.drop('rings',1), folds)
    return x_splits,y_splits

def split(data,split=0.75,folds=5):
    trainval,test = test_train_split(data,split)
    x_splits,y_split = cross_validation_split(trainval,folds)
    splits = x_splits,y_split
    return splits,test

trainval,test=split(data)
[x_splits,y_splits] = trainval
```

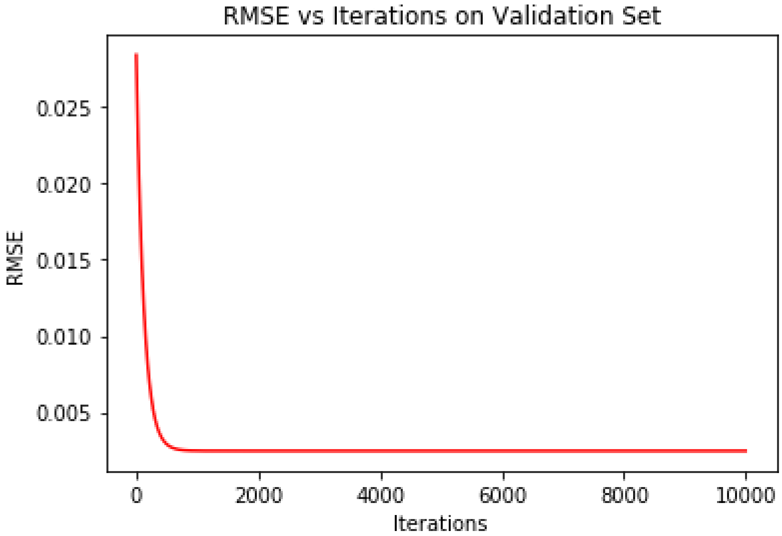
In [74]:

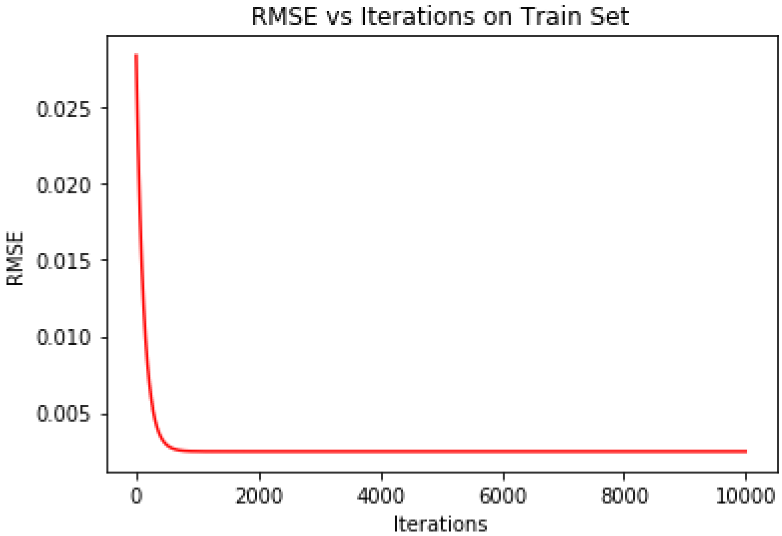
```
class LinearRegression:

    def __init__(self,x_in,y_in,folds=5):
        self.x_splits = x_in
        self.y_splits = y_in
        self.theta = np.zeros([1,self.x_splits[0].shape[1]+1])
        self.folds = folds

    def train(self,learning_rate=0.00005,iterations=1000,graph=True):
        if self.folds==1:
            train_score,theta = self.gradientDescend(learning_rate,iterations)
            return train_score,self.theta
        train_score,validation_score,theta = self.gradientDescend(learning_rate,iterati
ons)
        if graph:
            fig2, ax2 = plt.subplots()
            ax2.set_title("RMSE vs Iterations on Validation Set")
            ax2.plot(np.arange(iterations), validation_score, 'r')
            ax2.set_xlabel('Iterations')
            ax2.set_ylabel('RMSE')
            fig, ax = plt.subplots()
            ax.set_title("RMSE vs Iterations on Train Set")
            ax.plot(np.arange(iterations), train_score, 'r')
            ax.set_xlabel('Iterations')
            ax.set_ylabel('RMSE')
        return train_score[len(train_score)-1],validation_score[len(train_score)-1],sel
f.theta

    def fit(self):
        train_folds_score = np.zeros(self.folds)
        validation_folds_score = np.zeros(self.folds)
        if self.folds==1:
            x_csplits, y_csplits = x_splits.copy(), y_splits.copy()
            train_X,train_Y = pd.concat(x_csplits), pd.concat(y_csplits)
            train_Y = train_Y.values.reshape([train_Y.shape[0],1])
            ones = np.ones([train_X.shape[0],1])
            train_X = np.concatenate((ones,train_X),axis=1)
            a = np.linalg.inv(np.dot(train_X.T,train_X))
            b = np.dot(train_X.T,train_Y)
            self.theta = np.dot(a,b).T
            train_folds_score=(self.evaluate(train_X, train_Y))
            return train_folds_score,self.theta

        for fold in range(0, self.folds):
            x_csplits, y_csplits = x_splits.copy(), y_splits.copy()
            val_X,val_Y = x_csplits.pop(fold),y_csplits.pop(fold)
            train_X,train_Y = pd.concat(x_csplits), pd.concat(y_csplits)
            val_Y, train_Y= val_Y.values.reshape([val_Y.shape[0],1]), train_Y.values.re
shape([train_Y.shape[0],1])
            ones = np.ones([train_X.shape[0],1])
            train_X = np.concatenate((ones,train_X),axis=1)
            ones = np.ones([val_X.shape[0],1])
            val_X = np.concatenate((ones,val_X),axis=1)
            a = np.linalg.inv(np.dot(train_X.T,train_X))
            b = np.dot(train_X.T,train_Y)
            self.theta = np.dot(a,b).T
            train_folds_score[fold]=(self.evaluate(train_X, train_Y))
            validation_folds_score[fold]=(self.evaluate(val_X, val_Y))
        return train_folds_score,validation_folds_score,self.theta
```

```
    def gradientDescend(self,alpha=0.05,iterations=1000):
        if self.folds==1:
            train_score = np.zeros(iterations)
            validation_score = np.zeros(iterations)
            for i in range(iterations):
                train_folds_score = 0
                validation_folds_score = 0
                x_csplits, y_csplits = x_splits.copy(), y_splits.copy()
                train_X,train_Y = pd.concat(x_csplits), pd.concat(y_csplits)
                train_Y= train_Y.values.reshape([train_Y.shape[0],1])
                ones = np.ones([train_X.shape[0],1])
                train_X = np.concatenate((ones,train_X),axis=1)
                self.theta = self.theta - (alpha/len(train_X)) * np.sum(train_X.T.dot((
train_X @ self.theta.T - train_Y)), axis=0)
                print(self.theta)
                train_folds_score=(self.evaluate(train_X, train_Y))
            # print(train_folds_score,validation_folds_score)
            train_score[i]=train_folds_score
            return train_score,self.theta

        train_score = np.zeros(iterations)
        validation_score = np.zeros(iterations)
        for i in range(iterations):
            train_folds_score = np.zeros(self.folds)
            validation_folds_score = np.zeros(self.folds)

            for fold in range(0, self.folds):
                x_csplits, y_csplits = x_splits.copy(), y_splits.copy()
                val_X,val_Y = x_csplits.pop(fold),y_csplits.pop(fold)
                train_X,train_Y = pd.concat(x_csplits), pd.concat(y_csplits)
                val_Y, train_Y= val_Y.values.reshape([val_Y.shape[0],1]), train_Y.value
s.reshape([train_Y.shape[0],1])
                ones = np.ones([train_X.shape[0],1])
                train_X = np.concatenate((ones,train_X),axis=1)
                ones = np.ones([val_X.shape[0],1])
                val_X = np.concatenate((ones,val_X),axis=1)
                self.theta = self.theta - (alpha/len(train_X)) * np.sum(train_X.T.dot((
train_X @ self.theta.T - train_Y)), axis=0)
                train_folds_score[fold]=(self.evaluate(train_X, train_Y))
                validation_folds_score[fold]=(self.evaluate(val_X, val_Y))
            # print(train_folds_score,validation_folds_score)
            train_score[i]=(train_folds_score.mean())
            validation_score[i]=(validation_folds_score.mean())
        return train_score,validation_score,self.theta

    def predict(self,x):
        return np.dot(x,self.theta.T)

    def cost(self,X,Y):
        prediction = self.predict(X,self.theta)
        return ((prediction - Y)**2).mean()/2

    def rmse(self,X,Y):
        s = np.power(((X @ self.theta.T)-Y),2)
        return (np.sum(s)/(2 * len(X)))*(1/2)

    def evaluate(self,test_x, test_y):
        return self.rmse(test_x,test_y)
```

In [75]:

```
model = LinearRegression(x_splits,y_splits)
gd_train_score,gd_validation_score,theta = model.train(iterations=10000)
# print(gd_train_score,gd_validation_score,theta)
```





In [76]:

```
nf_train_score,nf_validation_score,theta = model.fit()
print(nf_train_score, nf_validation_score,theta)

print("Gradient Descend")
print("Train RMSE:",gd_train_score," ; Validation RMSE:",gd_validation_score)
print("Normal Equation")
print("Train RMSE:",nf_train_score," \nValidation RMSE:",nf_validation_score)
print("Train RMSE mean:",nf_train_score.mean()," ; Validation RMSE mean:",nf_validation
_score.mean())
```

```
[0.00142181 0.00150838 0.00150842 0.0014823  0.00147063] [0.00172245 0.001
37605 0.0013751  0.00148529 0.00152608] [[ 0.08162617  0.02400684 -0.02176
834  0.17811942  0.9418867   0.84487309
  -0.96126405 -0.32522167  0.32898957]]
Gradient Descend
Train RMSE: 0.0024676287519126506  ; Validation RMSE: 0.002467695229930739
Normal Equation
Train RMSE: [0.00142181 0.00150838 0.00150842 0.0014823  0.00147063]
Validation RMSE: [0.00172245 0.00137605 0.0013751  0.00148529 0.00152608]
Train RMSE mean: 0.0014783059613952005  ; Validation RMSE mean: 0.00149699
4118070164
```

Normal Equation RMSE < Gradient Descend RMSE

Regularisation

In [131]:

```
minfold = np.argmin(nf_validation_score)
print(minfold)
x_csplits, y_csplits = x_splits.copy(), y_splits.copy()
test_X,test_Y = x_csplits.pop(minfold),y_csplits.pop(minfold)
trainval_X,trainval_Y = pd.concat(x_csplits), pd.concat(y_csplits)
def cross_val_split(trainval_X,trainval_Y, folds=5):
    y_splits = np.array_split(trainval_Y, folds)
    x_splits = np.array_split(trainval_X, folds)
    return x_splits,y_splits
x_splits,y_splits = cross_val_split(trainval_X,trainval_Y, folds=5)
```

```
2
```

In [491]:

```python
from sklearn.linear_model import Ridge,Lasso
from sklearn.model_selection import GridSearchCV
alphas = np.array([1,0.1,0.01,0.001,0.0001,0.00001])
print("Ridge L2")
model = Ridge()
grid = GridSearchCV(estimator=model, param_grid=dict(alpha=alphas))
grid.fit(trainval_X, trainval_Y)
print(grid)
print("Best score",grid.best_score_)
print("Best estimator",grid.best_estimator_.alpha)
print("Lasso L1")
model = Lasso()
grid = GridSearchCV(estimator=model, param_grid=dict(alpha=alphas))
grid.fit(trainval_X, trainval_Y)
print(grid)
print("Best score",grid.best_score_)
print("Best estimator",grid.best_estimator_.alpha)
```

```
Ridge L2
GridSearchCV(cv='warn', error_score='raise-deprecating',
       estimator=Ridge(alpha=1.0, copy_X=True, fit_intercept=True, max_ite
r=None,
   normalize=False, random_state=None, solver='auto', tol=0.001),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid={'alpha': array([1.e+00, 1.e-01, 1.e-02, 1.e-03, 1.e-04,
1.e-05])},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=None, verbose=0)
Best score 0.4807807323713393
Best estimator 0.01
Lasso L1
GridSearchCV(cv='warn', error_score='raise-deprecating',
       estimator=Lasso(alpha=1.0, copy_X=True, fit_intercept=True, max_ite
r=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid={'alpha': array([1.e+00, 1.e-01, 1.e-02, 1.e-03, 1.e-04,
1.e-05])},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=None, verbose=0)
Best score 0.48051834808117094
Best estimator 1e-05

C:\Anaconda3\lib\site-packages\sklearn\model_selection\_split.py:2053: Fut
ureWarning: You should specify a value for 'cv' instead of relying on the
default value. The default value will change from 3 to 5 in version 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
C:\Anaconda3\lib\site-packages\sklearn\model_selection\_split.py:2053: Fut
ureWarning: You should specify a value for 'cv' instead of relying on the
default value. The default value will change from 3 to 5 in version 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
```

In [141]:

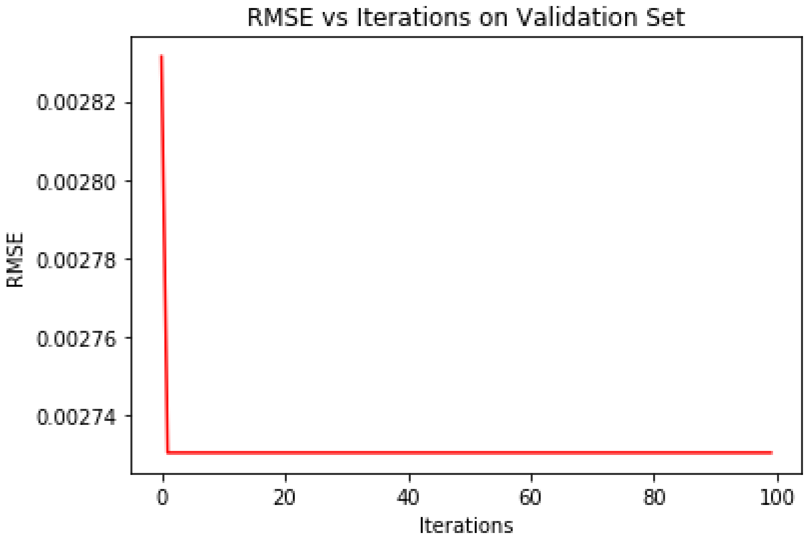
```
class RegLinearRegression:
    def __init__(self,x_in,y_in,folds=5):
        self.x_splits = x_in
        self.y_splits = y_in
        self.theta = np.zeros([1,self.x_splits[0].shape[1]+1])
        self.folds = folds

    def train(self,learning_rate=0.00005,iterations=1000,graph=True,regularization=None
,penalty=1):
        train_score,validation_score,theta = self.gradientDescend(learning_rate,iterati
ons,regularization,penalty)
        if graph:
            fig2, ax2 = plt.subplots()
            ax2.set_title("RMSE vs Iterations on Validation Set")
            ax2.plot(np.arange(iterations), validation_score, 'r')
            ax2.set_xlabel('Iterations')
            ax2.set_ylabel('RMSE')
            fig, ax = plt.subplots()
            ax.set_title("RMSE vs Iterations on Train Set")
            ax.plot(np.arange(iterations), train_score, 'r')
            ax.set_xlabel('Iterations')
            ax.set_ylabel('RMSE')
        return train_score[len(train_score)-1],validation_score[len(train_score)-1],sel
f.theta

    def fit(self):
        train_folds_score = np.zeros(self.folds)
        validation_folds_score = np.zeros(self.folds)
        for fold in range(0, self.folds):
            x_csplits, y_csplits = x_splits.copy(), y_splits.copy()
            val_X,val_Y = x_csplits.pop(fold),y_csplits.pop(fold)
            train_X,train_Y = pd.concat(x_csplits), pd.concat(y_csplits)
            val_Y, train_Y= val_Y.values.reshape([val_Y.shape[0],1]), train_Y.values.re
shape([train_Y.shape[0],1])
            ones = np.ones([train_X.shape[0],1])
            train_X = np.concatenate((ones,train_X),axis=1)
            ones = np.ones([val_X.shape[0],1])
            val_X = np.concatenate((ones,val_X),axis=1)
            a = np.linalg.inv(np.dot(train_X.T,train_X))
            b = np.dot(train_X.T,train_Y)
            self.theta = np.dot(a,b).T
            train_folds_score[fold]=(self.evaluate(train_X, train_Y))
            validation_folds_score[fold]=(self.evaluate(val_X, val_Y))
        return train_folds_score,validation_folds_score,self.theta

    def gradientDescend(self,alpha=0.05,iterations=1000,regularization=None,penalty=1):
        train_score = np.zeros(iterations)
        validation_score = np.zeros(iterations)
        for i in range(iterations):
            train_folds_score = np.zeros(self.folds)
            validation_folds_score = np.zeros(self.folds)

            for fold in range(0, self.folds):
                x_csplits, y_csplits = x_splits.copy(), y_splits.copy()
                val_X,val_Y = x_csplits.pop(fold),y_csplits.pop(fold)
                train_X,train_Y = pd.concat(x_csplits), pd.concat(y_csplits)
                val_Y, train_Y= val_Y.values.reshape([val_Y.shape[0],1]), train_Y.value
s.reshape([train_Y.shape[0],1])
                ones = np.ones([train_X.shape[0],1])
```

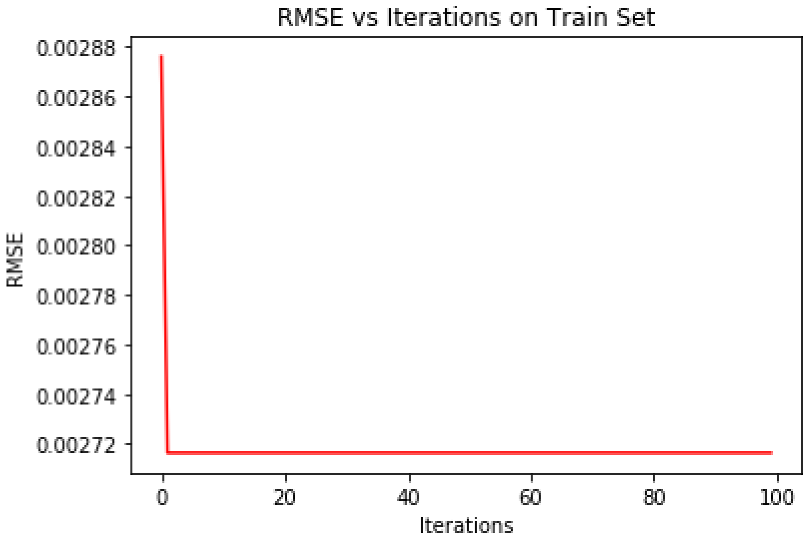
```
                train_X = np.concatenate((ones,train_X),axis=1)
                ones = np.ones([val_X.shape[0],1])
                val_X = np.concatenate((ones,val_X),axis=1)
                if regularization=='L2':
                    self.theta = self.theta - (alpha/len(train_X)) * (np.sum(train_X.T.
dot((train_X @ self.theta.T - train_Y)), axis=0)+penalty*np.sum(np.absolute(self.theta
)))
                elif regularization=='L1':
                    self.theta = self.theta - (alpha/len(train_X)) * (np.sum(train_X.T.
dot((train_X @ self.theta.T - train_Y)), axis=0)+penalty*np.sum(np.power(self.theta,2
)))
                else:
                    self.theta = self.theta - (alpha/len(train_X)) * np.sum(train_X.T.d
ot((train_X @ self.theta.T - train_Y)), axis=0)
                train_folds_score[fold]=(self.evaluate(train_X, train_Y))
                validation_folds_score[fold]=(self.evaluate(val_X, val_Y))
            # print(train_folds_score,validation_folds_score)
            train_score[i]=(train_folds_score.mean())
            validation_score[i]=(validation_folds_score.mean())
        return train_score,validation_score,self.theta

    def predict(self,x):
        return np.dot(x,self.theta.T)

    def cost(self,X,Y):
        prediction = self.predict(X,self.theta)
        return ((prediction - Y)**2).mean()/2

    def rmse(self,X,Y):
        s = np.power(((X @ self.theta.T)-Y),2)
        return (np.sum(s)/(2 * len(X)))*(1/2)

    def evaluate(self,test_x, test_y):
        return self.rmse(test_x,test_y)
```

Linear Regression with L2 regularization

In [142]:

```
model = RegLinearRegression(x_splits, y_splits, folds=5)
train_score, val_score, _ = model.train(learning_rate=0.01, iterations=100, regularizat
ion = 'L2', penalty = 2)
ones = np.ones([test_X.shape[0],1])
test_X_L2 = np.concatenate((ones,test_X),axis=1)
test_Y_L2 = test_Y.values.reshape([test_Y.shape[0],1])
test_score = model.evaluate(test_X_L2,test_Y_L2)
```





In [143]:

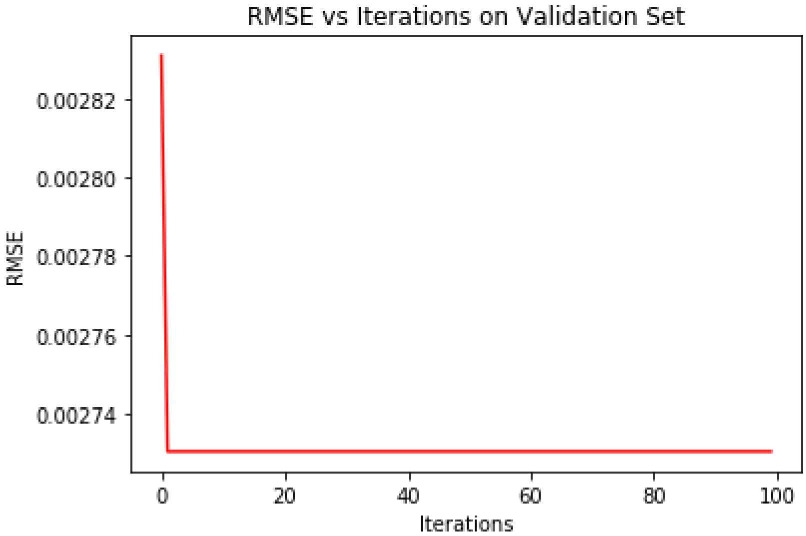
```
print("Train score",train_score,"Validation Score",val_score,"Test Score",test_score)
```

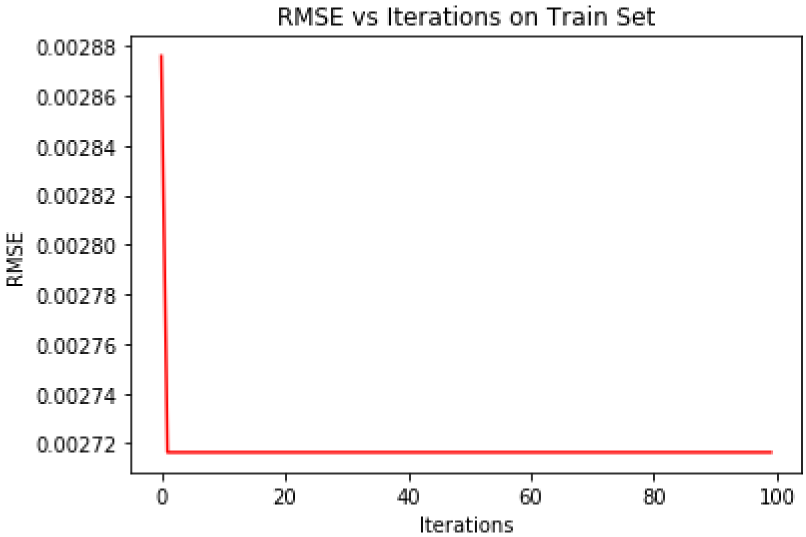
Train score 0.002716420479906825 Validation Score 0.00273040873208844 Test Score 0.0030012311145886654

Linear Regression with L2 regularization

In [145]:

```
model = RegLinearRegression(x_splits, y_splits, folds=5)
train_score, val_score, _ = model.train(learning_rate=0.05, iterations=100, regularization = 'L1', penalty = 2)
ones = np.ones([test_X.shape[0],1])
test_X_L1 = np.concatenate((ones,test_X),axis=1)
test_Y_L1 = test_Y.values.reshape([test_Y.shape[0],1])
test_score = model.evaluate(test_X_L1,test_Y_L1)
```





In [136]:

```
print("Train score",train_score,"Validation Score",val_score,"Test Score",test_score)
```

```
Train score 0.002716420479906825 Validation Score 0.00273040873208844 Test
Score 0.0030012311145886654
```

Best Fit Line

In [478]:

```
dataset_location = 'bodybrainw/data.csv'
data = pd.read_csv(dataset_location)
# data = (data-data.min())/(data.max()-data.min())
data.head()
```

Out[478]:

	Brain_Weight	Body_Weight
0	1.0	8.429338
1	1.6	10.516225
2	2.2	12.339744
3	2.8	19.217969
4	3.4	19.749753

In [479]:

```
splits = np.array_split(data, 1)
y_splits = np.array_split(data['Brain_Weight'], 1)
x_splits = np.array_split(data.drop('Brain_Weight',1), 1)
train_x = data['Brain_Weight'].values
train_y = data.drop('Brain_Weight',1).values
```

In [480]:

```
class SimpleLinearRegression:
    def __init__ (self, x_in, y_in):
        self.X = x_in
        self.Y = y_in
        self.theta = np.array([[1.0, 1.0]])
    def train(self,learning_rate=0.005,iterations=10000,regularization=None,penalty=1):
        theta = np.array([[1.0, 1.0]])
        self.X = (np.array(self.X).reshape(-1,1))
        ones = np.ones([self.X.shape[0], 1])
        self.X = np.concatenate([ones, self.X],1)
        self.Y = (np.array(self.Y).reshape(-1,1))
        print(self.X.shape,self.Y.shape, regularization,penalty)
        rmse,self.theta = self.gradient_descent(learning_rate, iterations,regularizatio
n,penalty)
        print("[m,c]:",self.theta," RMSE:", rmse)
        slope = self.theta[0][0]
        constant = self.theta[0][1]
        return slope,constant

    def predict(self,x):
        slope = self.theta[0][0]
        constant = self.theta[0][1]
        y = slope* x + constant
        return y

    def rmse(self,X,Y):
        s = np.power(((X @ self.theta.T)-Y),2)
        return (np.sum(s)/(2 * len(X)))*(1/2)

    def gradient_descent(self, alpha=0.0005,iterations=1000,regularization=None,penalty
=1):
        for i in range(iterations):
            # theta = theta - (alpha/len(X)) * np.sum((X @ theta.T - y) * X, axis=0)
            # print(self.X.shape,self.Y.shape,self.theta.shape,self.theta)
            if regularization=='L2':
                    self.theta = self.theta - (alpha/len(self.X)) * (np.sum((self.X @ s
elf.theta.T - self.Y)* self.X, axis=0)+penalty*np.sum(np.absolute(self.theta)))
            elif regularization=='L1':
                self.theta = self.theta - (alpha/len(self.X)) * (np.sum((self.X @ self.
theta.T - self.Y)* self.X, axis=0)+penalty*np.sum(np.power(self.theta,2)))
            else:
                self.theta = self.theta - (alpha/len(self.X)) * np.sum((self.X @ self.t
heta.T - self.Y)* self.X, axis=0)
            error = self.rmse(self.X, self.Y)
        return (error,self.theta)
```

In [481]:

```
model = SimpleLinearRegression(train_x,train_y)
modell1 = SimpleLinearRegression(train_x,train_y)
modell2 = SimpleLinearRegression(train_x,train_y)
```

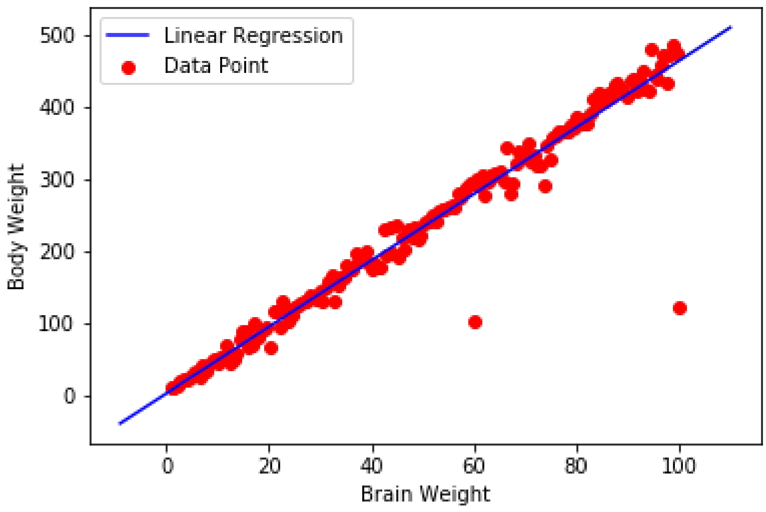
In [482]:

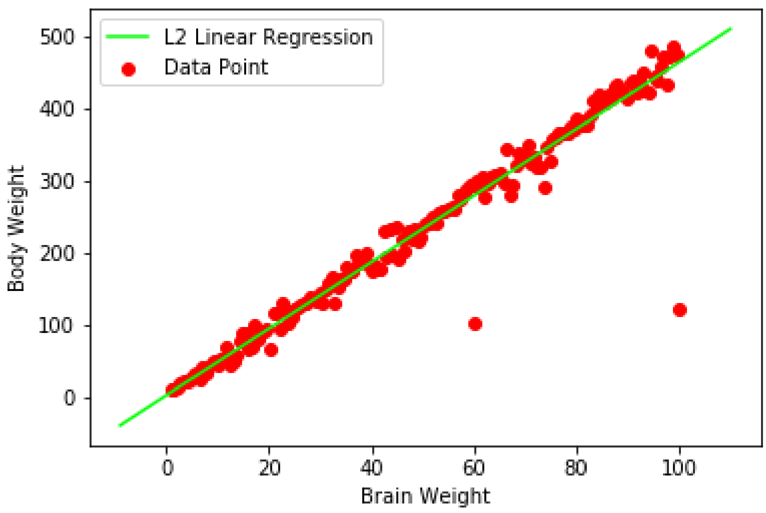
```
theta = model.train(learning_rate=0.0005,iterations=1000)
thetal1 = modell1.train(learning_rate=0.0005,iterations=1000,regularization='L1',penalt
y=100)
thetal2 = modell2.train(learning_rate=0.0005,iterations=1000,regularization='L2',penalt
y=100)
```

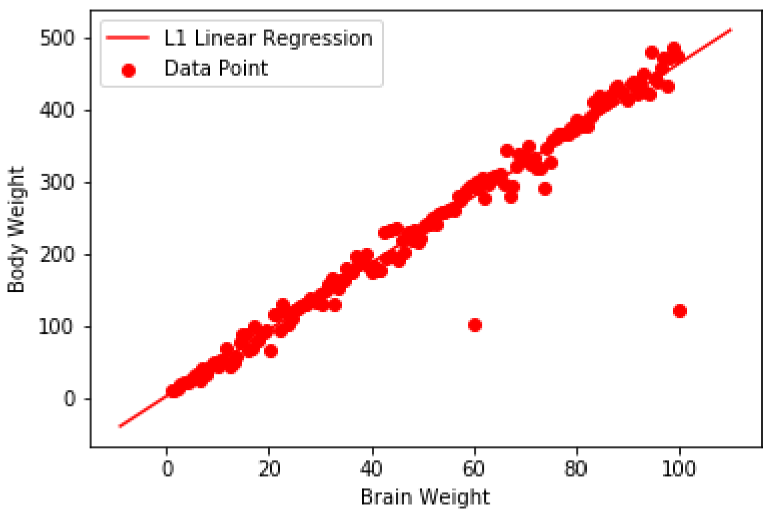
```
(167, 2) (167, 1) None 1
[m,c]: [[1.48381831 4.6153523 ]]  RMSE: 269.90315523919077
(167, 2) (167, 1) L1 100
[m,c]: [[-7.59255968  4.73682482]]  RMSE: 278.757396860283
(167, 2) (167, 1) L2 100
[m,c]: [[0.05699742 4.63586253]]  RMSE: 270.60416385762323
```

In [483]:

```
b0,b1=theta[0],theta[1]
b0l1,b1l1=thetal1[0],thetal1[1]
b0l2,b1l2=thetal2[0],thetal2[1]
x_max = np.max(train_x) + 10
x_min = np.min(train_x) - 10
x = np.linspace(x_min, x_max, 1000)
y = b0 + b1 * x
yl1 = b0l1 + b1l1 * x
yl2 = b0l2 + b1l2 * x
plt.plot(x, y, color='#0000ff', label='Linear Regression')
plt.scatter(train_x, train_y, color='#ff0000', label='Data Point')
plt.xlabel('Brain Weight')
plt.ylabel('Body Weight')
plt.legend()
plt.show()
plt.plot(x, y, color='#00ff00', label='L2 Linear Regression')
plt.scatter(train_x, train_y, color='#ff0000', label='Data Point')
plt.xlabel('Brain Weight')
plt.ylabel('Body Weight')
plt.legend()
plt.show()
plt.plot(x, y, color='#ff0000', label='L1 Linear Regression')
plt.scatter(train_x, train_y, color='#ff0000', label='Data Point')
plt.xlabel('Brain Weight')
plt.ylabel('Body Weight')
plt.legend()
plt.show()
```







Non regularized line was the best fit among the three in train set and has lowest RMSE, but the model would probable overfit.

In real world scenario L1 regularisation might be better