Machine Learning lab

Lab 06

Exercise 0: Dataset Preprocessing

Importing Packages

In [1]:

```
import pandas as pd                                    #Importing Pandas
import numpy as np                                     #Importing Numpy
import matplotlib.pyplot as plt                        #Importing Matplotlib
import math                                            #Importing Math
from sklearn.model_selection import train_test_split   #Importing Sklearn Train Te
from sklearn.linear_model import SGDRegressor          #Importing Sklearn Stochast
from sklearn.preprocessing import StandardScaler       #Importing Sklearn Standard
from sklearn.metrics import mean_squared_error         #Importing Sklearn Mean Squ
from sklearn.model_selection import GridSearchCV       #Importing Sklearn Grid Sea
from sklearn.preprocessing import PolynomialFeatures   #Importing Polynomial Featu
from sklearn.linear_model import LinearRegression, Ridge #Importing Linear Regressio
```

Generating a Sample dataset called D1

In [2]:

```
#Mean of Normal Distribution
mu = 1

#Standard Deviation of Normal Distribution
sigma = 0.05

#Generating Matrix X through Normal Distribution
X = np.random.normal(mu,sigma,size = (100,1))
```

In [3]:

```
#Generating Matrix Y using the following function:
# y = 1.3x^2 + 4.8x + 8 + ψ
Y = 1.3 * (X ** 2) + 4.8 * X + 8 + np.random.rand(100,1)
```

Importing Wine Quality Dataset called D2

In [4]:

```
wine_quality = pd.read_csv('winequality-red.csv',sep=';')
wine_quality.head()
```

Out[4]:

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

In [5]:
```
#Checking the description of the wine quality dataset
wine_quality.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         1599 non-null   float64
 1   volatile acidity      1599 non-null   float64
 2   citric acid           1599 non-null   float64
 3   residual sugar        1599 non-null   float64
 4   chlorides             1599 non-null   float64
 5   free sulfur dioxide   1599 non-null   float64
 6   total sulfur dioxide  1599 non-null   float64
 7   density               1599 non-null   float64
 8   pH                    1599 non-null   float64
 9   sulphates             1599 non-null   float64
 10  alcohol               1599 non-null   float64
 11  quality               1599 non-null   int64  
dtypes: float64(11), int64(1)
memory usage: 150.0 KB
```

Exercise 1: Generalized Linear Models with Scikit Learn

Splitting the data into Train and Test Splits according to the 80%:20% ratio. Using dataset D2

In [6]:
```
#Initalizing our Random seed so that our results are consistent
random_seed = 3116
```

Splitting Dataset

In [7]:
```
#Creating Matrix X for wine quality dataset by dropping label column
wine_quality_X = wine_quality.drop('quality',axis=1)

#Creating Matrix Y for wine quality dataset consisting of only label column
wine_quality_Y = wine_quality['quality']

#Using Train test split from Sklearn package to split my Matrix X and Matrix Y into
X_train, X_test, y_train, y_test = train_test_split(wine_quality_X, wine_quality_Y,
```

Standardization and Normalization of Dataset

In [8]:
```
#Creating an Object of Standard Scalar from Sklearn for Normalizing my dataset
scalar = StandardScaler()

#Normalizing X_train
X_train = scalar.fit_transform(X_train)

#Normalizing X_test
X_test = scalar.fit_transform(X_test)
```

Picking three sets of hyperparameters and learning each model (without cross validation)

Initialization of Alpha's and Lambda's

In [9]:
```
#Initializing different values of alpha's in a list
```

```
alphas = [0.01,0.001,0.0001]

#Initializing different values of lambda's in a list
lambdas = [np.exp(-10),np.exp(-11),np.exp(-12)]
```

Function to fit Linear Model using Stochastic Gradient Descent as an Optimizer

In [10]:

```
def linear_models_SGD(X_train, y_train, X_test, y_test, penalty_, alphas, lambdas):
    #Initializing Multi-dimensional array to store Training RMSE's
    train_rmse = np.zeros(shape=(len(alphas),))

    #Initializing Multi-dimensional array to store Test RMSE's
    test_rmse = np.zeros(shape=(len(alphas),))

    #Initializing counter for rmse array with 0
    i = 0

    #Iterating over all combinations of Alpha's and Lambda's
    for alpha,lamda in zip(alphas,lambdas):
        #Creating a Model with different Parameters and SGD as an Optimizer
        model = SGDRegressor(loss='squared_loss',penalty=penalty_,random_state=rando

        #Fitting the created model on the Training dataset
        model.fit(X_train,y_train)

        #Calculating and Storing the Training RMSE on the Training dataset
        train_rmse[i] = mean_squared_error(y_train,model.predict(X_train),squared=Fa

        #Calculating and Storing the Test RMSE on the Training dataset
        test_rmse[i] = mean_squared_error(y_test,model.predict(X_test),squared=False

        #Incrementing counter by 1
        i += 1

    #Returning the Training and Test RMSE's array
    return train_rmse,test_rmse
```

Ordinary Least Squares

In [11]:

```
#Fitting Ordinary Least Squares Model with SGD
ols_train_rmse, ols_test_rmse = linear_models_SGD(X_train, y_train, X_test, y_test,

print('The Minimum Train RMSE of Ordinary Least Square is : {} having Alpha: {} and
      .format(min(ols_train_rmse),alphas[np.argmin(ols_train_rmse)],0))
print('The Minimum Test RMSE of Ordinary Least Square is : {} having Alpha: {} and L
      .format(min(ols_test_rmse),alphas[np.argmin(ols_test_rmse)],0))
```

```
The Minimum Train RMSE of Ordinary Least Square is : 0.6364969003941113 having Alph
a: 0.001 and Lambda: 0
The Minimum Test RMSE of Ordinary Least Square is : 0.6888244104023411 having Alpha:
0.001 and Lambda: 0
```

Ridge Regression

In [12]:

```
#Fitting Ridge Regression Model with SGD
rr_train_rmse, rr_test_rmse = linear_models_SGD(X_train, y_train, X_test, y_test, 'l

print('The Minimum Train RMSE of Ridge Regression is : {} having Alpha: {} and Lambd
      .format(min(rr_train_rmse),alphas[np.argmin(rr_train_rmse)],lambdas[np.argmin(
print('The Minimum Test RMSE of Ridge Regression is : {} having Alpha: {} and Lambda
      .format(min(rr_test_rmse),alphas[np.argmin(rr_test_rmse)],lambdas[np.argmin(rr
```

```
The Minimum Train RMSE of Ridge Regression is : 0.6364968787707496 having Alpha: 0.0
01 and Lambda: 1.670170079024566e-05
The Minimum Test RMSE of Ridge Regression is : 0.6888237000202886 having Alpha: 0.00
1 and Lambda: 1.670170079024566e-05
```

LASSO

In [13]:

```
#Fitting LASSO Regression Model with SGD
lasso_train_rmse, lasso_test_rmse = linear_models_SGD(X_train, y_train, X_test, y_te

print('The Minimum Train RMSE of LASSO Regression is : {} having Alpha: {} and Lambd
      .format(min(lasso_train_rmse),alphas[np.argmin(lasso_train_rmse)],lambdas[np.a
print('The Minimum Test RMSE of LASSO Regression is : {} having Alpha: {} and Lambda
      .format(min(lasso_test_rmse),alphas[np.argmin(lasso_test_rmse)],lambdas[np.arg
```

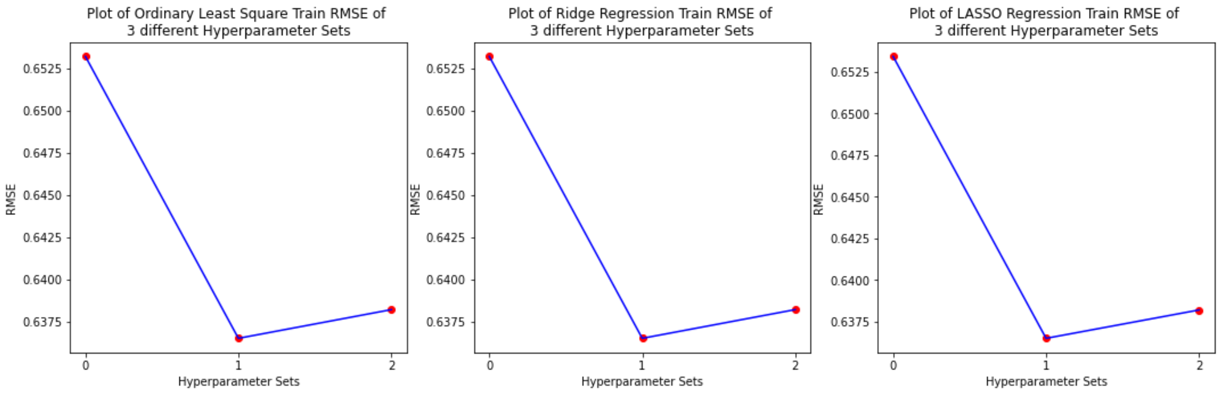
```
The Minimum Train RMSE of LASSO Regression is : 0.6364969383590316 having Alpha: 0.0
01 and Lambda: 1.670170079024566e-05
The Minimum Test RMSE of LASSO Regression is : 0.688820228884294 having Alpha: 0.001
and Lambda: 1.670170079024566e-05
```

Plotting Train and Test RMSE on one plot

Plotting Train RMSE's Separately

In [14]:

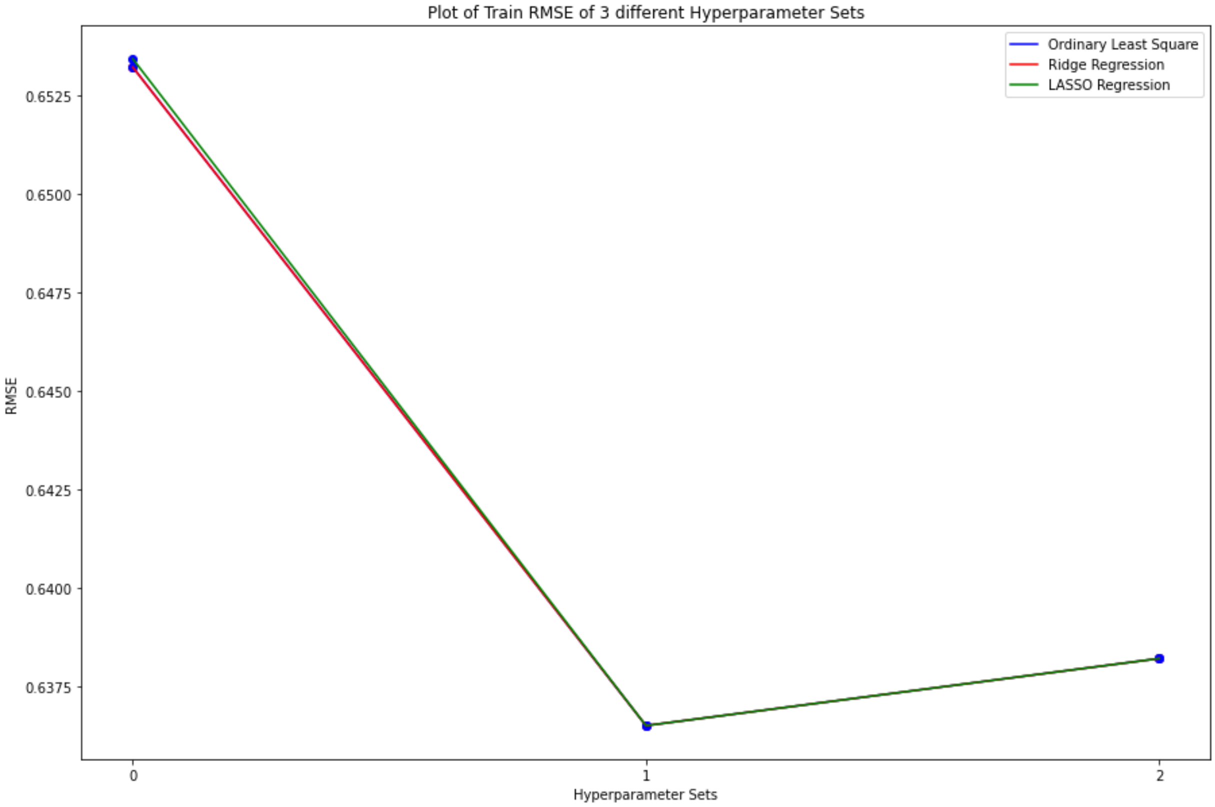
```
fig = plt.figure(figsize=(18,5))

#Plot of Ordinary Least Squares
plt.subplot(131)
plt.plot(ols_train_rmse,c='b')
plt.scatter(np.arange(0, 3),ols_train_rmse,c='r')
plt.xlabel('Hyperparameter Sets')
plt.ylabel('RMSE')
plt.title('Plot of Ordinary Least Square Train RMSE of \n3 different Hyperparameter
plt.xticks(np.arange(0, 3))

#Plot of Ridge Regression
plt.subplot(132)
plt.plot(rr_train_rmse,c='b')
plt.scatter(np.arange(0, 3),rr_train_rmse,c='r')
plt.xlabel('Hyperparameter Sets')
plt.ylabel('RMSE')
plt.title('Plot of Ridge Regression Train RMSE of \n3 different Hyperparameter Sets'
plt.xticks(np.arange(0, 3))

#Plot of LASSO Regression
plt.subplot(133)
plt.plot(lasso_train_rmse,c='b')
plt.scatter(np.arange(0, 3),lasso_train_rmse,c='r')
plt.xlabel('Hyperparameter Sets')
plt.ylabel('RMSE')
plt.title('Plot of LASSO Regression Train RMSE of \n3 different Hyperparameter Sets'
plt.xticks(np.arange(0, 3))

plt.show()
```



Plotting Combined Train RMSE's

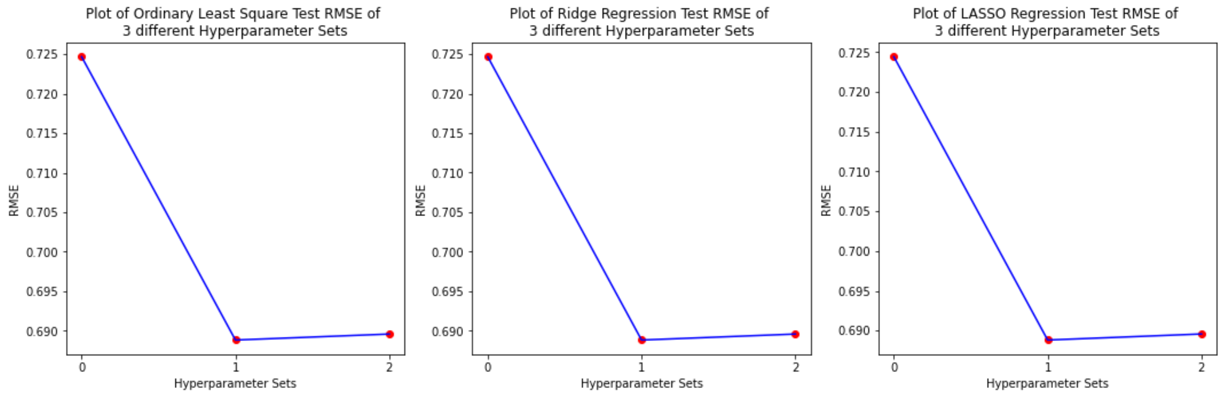
In [15]:

```
fig = plt.figure(figsize=(15,10))
plt.subplot(111)

#Plot of Ordinary Least Squares
plt.plot(ols_train_rmse,c='b',label='Ordinary Least Square')
plt.scatter(np.arange(0, 3),ols_train_rmse,c='r')

#Plot of Ridge Regression
plt.plot(rr_train_rmse,c='r',label='Ridge Regression')
plt.scatter(np.arange(0, 3),rr_train_rmse,c='b')

#Plot of LASSO Regression
plt.plot(lasso_train_rmse,c='g',label='LASSO Regression')
plt.scatter(np.arange(0, 3),lasso_train_rmse,c='b')

#Setting parameter values for Graph
plt.xlabel('Hyperparameter Sets')
plt.ylabel('RMSE')
plt.title('Plot of Train RMSE of 3 different Hyperparameter Sets')
plt.xticks(np.arange(0, 3))
plt.legend(loc = 1)

plt.show()
```



Plotting Test RMSE's Separately

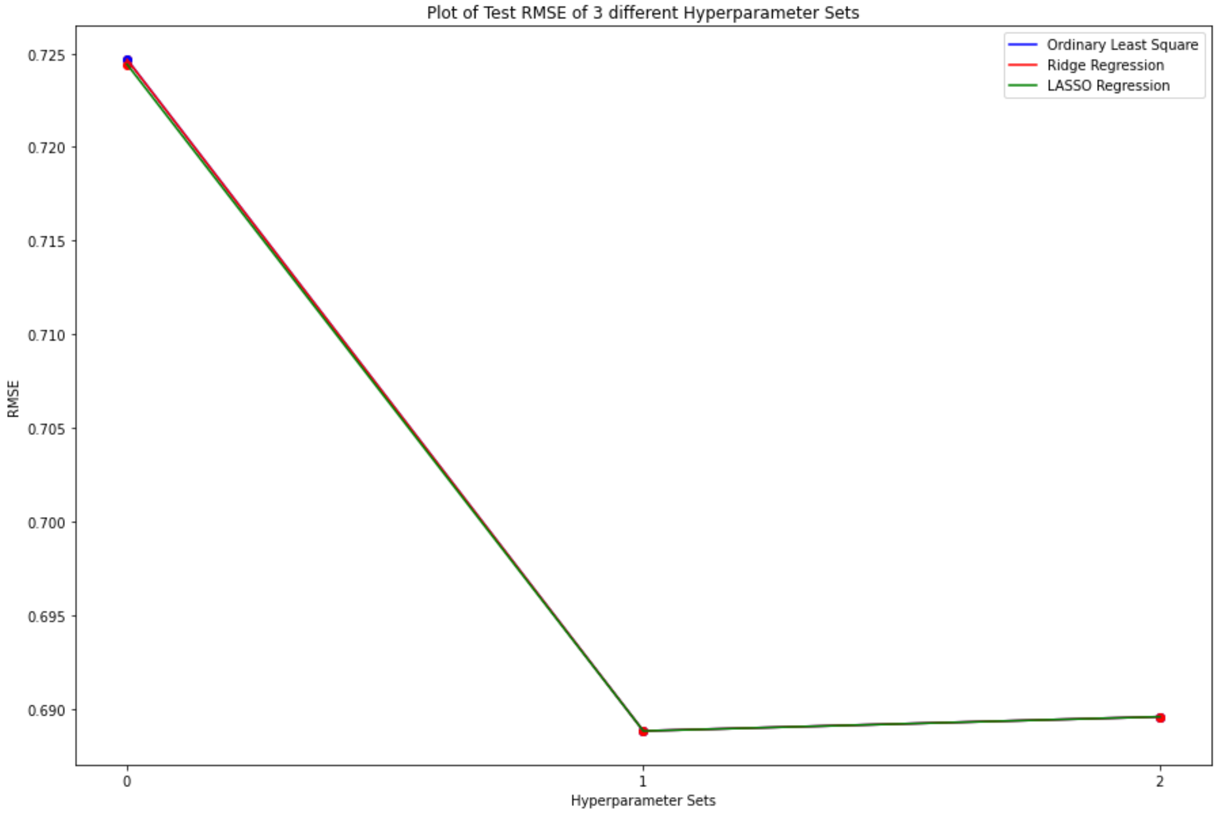
In [16]:
```
fig = plt.figure(figsize=(18,5))

#Plot of Ordinary Least Squares
plt.subplot(131)
plt.plot(ols_test_rmse,c='b')
plt.scatter(np.arange(0, 3),ols_test_rmse,c='r')
plt.xlabel('Hyperparameter Sets')
plt.ylabel('RMSE')
plt.title('Plot of Ordinary Least Square Test RMSE of \n3 different Hyperparameter S
plt.xticks(np.arange(0, 3))

#Plot of Ridge Regression
plt.subplot(132)
plt.plot(rr_test_rmse,c='b')
plt.scatter(np.arange(0, 3),rr_test_rmse,c='r')
plt.xlabel('Hyperparameter Sets')
plt.ylabel('RMSE')
plt.title('Plot of Ridge Regression Test RMSE of \n3 different Hyperparameter Sets')
plt.xticks(np.arange(0, 3))

#Plot of LASSO Regression
plt.subplot(133)
plt.plot(lasso_test_rmse,c='b')
plt.scatter(np.arange(0, 3),lasso_test_rmse,c='r')
plt.xlabel('Hyperparameter Sets')
plt.ylabel('RMSE')
plt.title('Plot of LASSO Regression Test RMSE of \n3 different Hyperparameter Sets')
plt.xticks(np.arange(0, 3))

plt.show()
```



Plotting Combined Test RMSE's

In [17]:

```
fig = plt.figure(figsize=(15,10))
plt.subplot(111)

#Plot of Ordinary Least Squares
plt.plot(ols_test_rmse,c='b',label='Ordinary Least Square')
plt.scatter(np.arange(0, 3),ols_test_rmse,c='r')

#Plot of Ridge Regression
plt.plot(rr_test_rmse,c='r',label='Ridge Regression')
plt.scatter(np.arange(0, 3),rr_test_rmse,c='b')

#Plot of LASSO Regression
plt.plot(lasso_test_rmse,c='g',label='LASSO Regression')
plt.scatter(np.arange(0, 3),lasso_test_rmse,c='r')

#Setting Parameters for the Graph
plt.xlabel('Hyperparameter Sets')
plt.ylabel('RMSE')
plt.title('Plot of Test RMSE of 3 different Hyperparameter Sets')
plt.xticks(np.arange(0, 3))
plt.legend(loc = 1)

plt.show()
```



Tuning the hyperparameters using scikit learn GridSearchCV and plotting the results of cross validation for each model

Function to perform Grid Search over the range of parameters

In [18]:

```
def grid_search(X_train, y_train, X_test, y_test, penalty_, alphas, lambdas,max_iter
    #Creating a dictionary containing different values for different hyperparameter
    params = {'eta0' : alphas,
              'alpha' : lambdas}

    #Creating a GridSearchCV object with all the required configurations and hyperpa
    model = GridSearchCV(SGDRegressor(loss='squared_loss',penalty=penalty_,max_iter=

    #Fitting the GridSearchCV model on the Training dataset
    model.fit(X_train,y_train)

    #Calculating and Storing the Training RMSE on the Training dataset
    train_rmse = model.cv_results_['mean_train_score']

    #Calculating and Storing the Test RMSE on the Training dataset
    test_rmse = model.cv_results_['mean_test_score']

    ##Returning the GridSearch Model,Training and Test RMSE's array
    return model, train_rmse,test_rmse
```

Ordinary Least Squares

In [19]:

```
#Fitting Ordinary Least Squares Model with SGD and GridSearchCV
ols_model, ols_train_rmse, ols_test_rmse = grid_search(X_train,y_train,X_test,y_test

print('The Minimum Train RMSE of Ordinary Least Square is : {} having Alpha: {} and
      .format(min(ols_train_rmse),ols_model.best_params_['eta0'],ols_model.best_para
print('The Minimum Test RMSE of Ordinary Least Square is : {} having Alpha: {} and L
      .format(min(ols_test_rmse),ols_model.best_params_['eta0'],ols_model.best_param
```

```
The Minimum Train RMSE of Ordinary Least Square is : -0.007852409844261766 having Al
```

```
pha: 0.01 and Lambda: 0
The Minimum Test RMSE of Ordinary Least Square is : -0.049986819987276276 having Alp
ha: 0.01 and Lambda: 0
```

Ridge Regression

In [20]:

```python
#Fitting Ridge Regression Model with SGD and GridSearchCV
rr_model, rr_train_rmse, rr_test_rmse = grid_search(X_train,y_train,X_test,y_test,'l

print('The Minimum Train RMSE of Ridge Regression is : {} having Alpha: {} and Lambd
      .format(min(rr_train_rmse),rr_model.best_params_['eta0'],rr_model.best_params_
print('The Minimum Test RMSE of Ridge Regression is : {} having Alpha: {} and Lambda
      .format(min(rr_test_rmse),rr_model.best_params_['eta0'],rr_model.best_params_[
```

```
The Minimum Train RMSE of Ridge Regression is : -0.007824497975728217 having Alpha:
0.01 and Lambda: 1.670170079024566e-05
The Minimum Test RMSE of Ridge Regression is : -0.050001974240981364 having Alpha:
0.01 and Lambda: 1.670170079024566e-05
```

LASSO

In [21]:

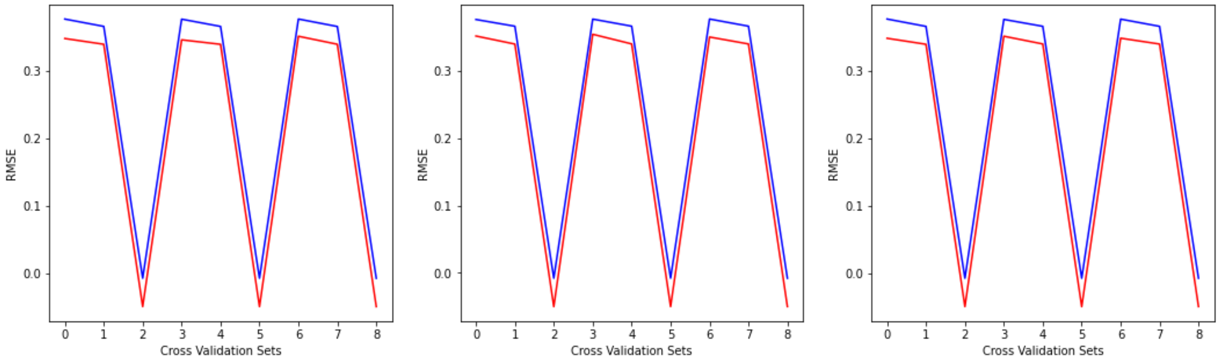
```python
#Fitting LASSO Model with SGD and GridSearchCV
lasso_model, lasso_train_rmse, lasso_test_rmse = grid_search(X_train,y_train,X_test,

print('The Minimum Train RMSE of LASSO Regression is : {} having Alpha: {} and Lambd
      .format(min(lasso_train_rmse),lasso_model.best_params_['eta0'],lasso_model.bes
print('The Minimum Test RMSE of LASSO Regression is : {} having Alpha: {} and Lambda
      .format(min(lasso_test_rmse),lasso_model.best_params_['eta0'],lasso_model.best
```

```
The Minimum Train RMSE of LASSO Regression is : -0.00782096944721189 having Alpha:
0.01 and Lambda: 1.670170079024566e-05
The Minimum Test RMSE of LASSO Regression is : -0.04998832257736063 having Alpha: 0.
01 and Lambda: 1.670170079024566e-05
```

Plotting the results of cross validation on each Model

In [22]:

```python
fig = plt.figure(figsize=(18,5))

#Plot of Ordinary Least Squares
plt.subplot(131)
plt.plot(ols_train_rmse,c='b')
plt.plot(ols_test_rmse,c='r')
plt.xlabel('Cross Validation Sets')
plt.ylabel('RMSE')

#Plot of Ridge Regression
plt.subplot(132)
plt.plot(rr_train_rmse,c='b')
plt.plot(rr_test_rmse,c='r')
plt.xlabel('Cross Validation Sets')
plt.ylabel('RMSE')

#Plot of LASSO Regression
plt.subplot(133)
plt.plot(lasso_train_rmse,c='b')
#Scatter plot of Ridge Regression
plt.plot(lasso_test_rmse,c='r')
plt.xlabel('Cross Validation Sets')
plt.ylabel('RMSE')

plt.show()
```



Using the optimal hyperparameter, evaluating each model on the Test Set.

From the above Models and Graph's, we get the following Optimal Hyperparameters: For Ordinary Least Square: Alpha: 0.01 Lambda: 0 For Ridge Regression: Alpha: 0.01 Lambda: 1.670170079024566e-05 For LASSO Regression: Alpha: 0.01 Lambda: 1.670170079024566e-05

Ordinary Least Squares

In [23]:
```
best_alpha_ols = 0.01
best_lambda_ols = 0
```

In [24]:
```
#Initializing the Ordinary Least Square Model with Best and Optimal Hyperparameters
ols_model = SGDRegressor(loss='squared_loss',penalty='none',random_state=random_seed

#Fitting the created model on the Test dataset
ols_model.fit(X_test,y_test)

#Calculating and Storing the Test RMSE on the Test dataset
print('The Test RMSE of Ordinary Least Square on Optimal Parameters is: {}'.format(m
```

```
The Test RMSE of Ordinary Least Square on Optimal Parameters is: 0.6785250119747812
```

Ridge Regression

In [25]:
```
best_alpha_rr = 0.01
best_lambda_rr = 1.670170079024566e-05
```

In [26]:
```
#Initializing the Ridge Regression Model with Best and Optimal Hyperparameters
rr_model = SGDRegressor(loss='squared_loss',penalty='l2',random_state=random_seed,le

#Fitting the created model on the Test dataset
rr_model.fit(X_test,y_test)

#Calculating and Storing the Test RMSE on the Test dataset
print('The Test RMSE of Ridge Regression on Optimal Parameters is: {}'.format(mean_s
```

```
The Test RMSE of Ridge Regression on Optimal Parameters is: 0.6785250904970329
```

LASSO Regression

In [27]:
```
best_alpha_lasso = 0.01
best_lambda_lasso = 1.670170079024566e-05
```

In [28]:
```
#Initializing the LASSO Regression Model with Best and Optimal Hyperparameters
lasso_model = SGDRegressor(loss='squared_loss',penalty='l1',random_state=random_seed

#Fitting the created model on the Test dataset
```

```
lasso_model.fit(X_test,y_test)

#Calculating and Storing the Test RMSE on the Test dataset
print('The Test RMSE of LASSO Regression on Optimal Parameters is: {}'.format(mean_s
```

```
The Test RMSE of LASSO Regression on Optimal Parameters is: 0.6785370573881958
```

Exercise 2: Higher Order Polynomial Regression

Task A: Prediction with high degree of polynomials

Function to Fit Multidimensional Linear Regression with given degree on the dataset

In [29]:

```
def fit_multidimensional_model(X_train ,y_train, degree):
    #Creating the object of PolynomialFeatures with the provided degree
    p = PolynomialFeatures(degree = degree)

    #Fitting and Transforming our dataset into the multidimensional features
    data = p.fit_transform(X_train ,y_train)

    #Creating and Fitting a Linear Regression model on our created Polynomial Featur
    poly_reg = LinearRegression().fit(data ,y_train)

    #Calculating our Predicted Y using our Fitted Linear regression Model
    y_pred = poly_reg.predict(data)

    #Returning our Predicted Y
    return y_pred
```

Function to Plot our Fitted Multidimensional Linear Regression Models

In [30]:

```
def plot_multdimensional_model(X_train ,y_train ,y_pred_list ,fig_title ,plot_titles
    #Calculating number of Rows and Columns for Plotting multiple Graphs as a Subplo
    rows, cols = math.ceil(y_pred_list.shape[1]/2) , 2

    #Initializing index for our Subplot to 1
    subplot_index = 1

    #Creating a Figure with specific Size and a Title
    fig = plt.figure(figsize = (15,15))
    fig.suptitle(fig_title ,fontsize = 16)

    #Iterating over all the provided Y predicted where each Y_pred represent differe
    for i in range(len(y_pred_list[0])):
        #Creating a subplot with specific Index
        plt.subplot(rows ,cols ,subplot_index)

        #Plotting the scatter plot containing our Original Dataset points
        plt.scatter(X_train ,y_train ,label = 'Original Data')

        #Sorting and Zipping our X matrix and Predicted Y for Plotting our Linear Re
        sor_features = sorted(zip(X_train ,y_pred_list[:,i]))
        x_poly, poly_pred = zip(*sor_features)

        #Plotting a line plot representing our Fitted Polynomial Linear Regression
        plt.plot(x_poly ,poly_pred ,c = 'r' ,label = 'Fitted Polynomial Approximatio

        #Setting values of different Parameters for our Graph
        plt.xlabel('X')
        plt.ylabel('Y')
        plt.title(plot_titles[i])
        plt.legend()
```

```
        #Incrementing the Index for our Subplot by 1
        subplot_index += 1

    #Showing our Creating Figure containing all the Subplots
    plt.show()
```

Fitting the Polynomial Linear Regression with Different Degree's on our Dataset

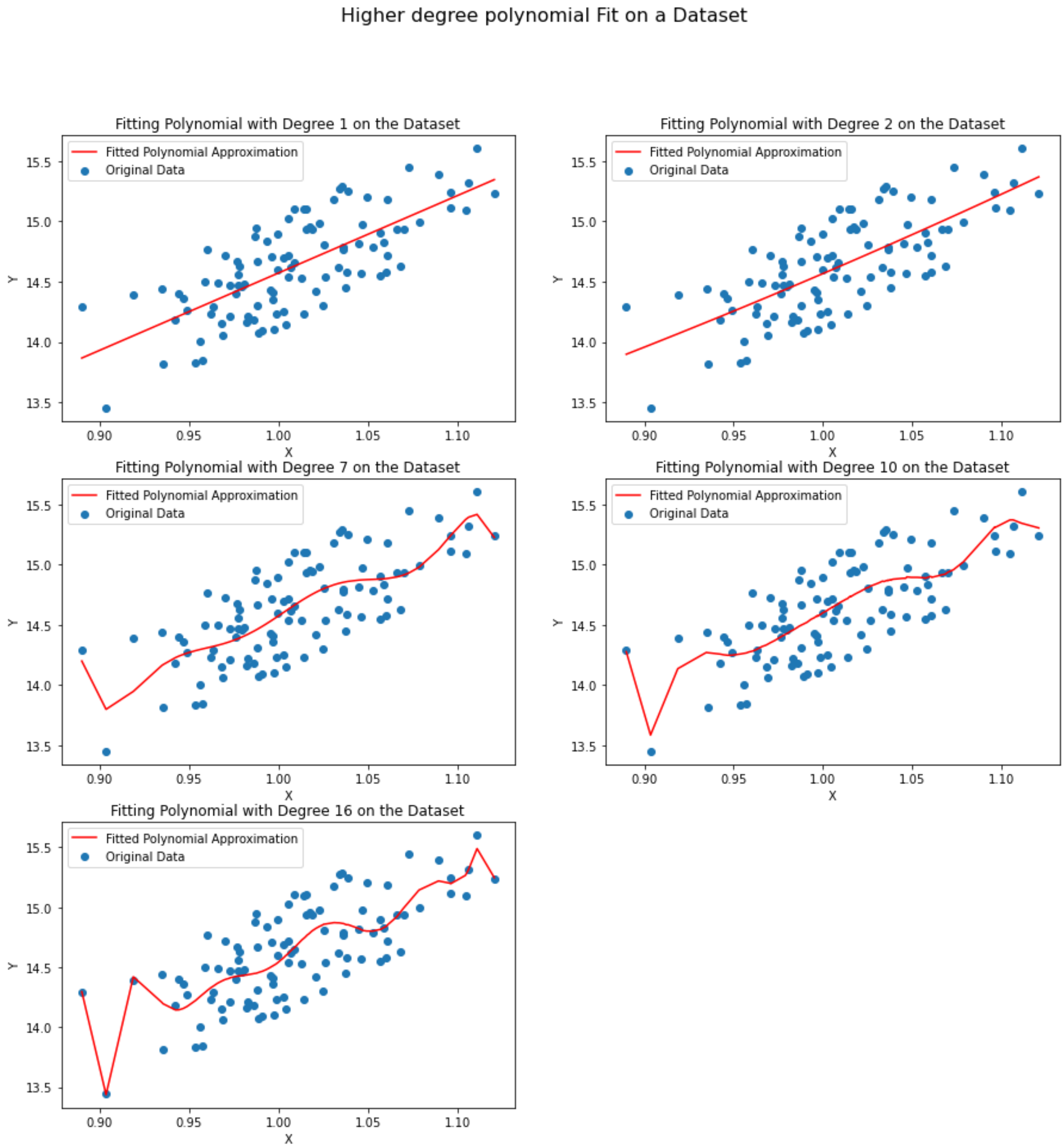
In [31]:
```
#Fitting Polynomial with Degree 1 on our Dataset
p1_y_pred = fit_multidimensional_model(X ,Y ,1)

#Fitting Polynomial with Degree 2 on our Dataset
p2_y_pred = fit_multidimensional_model(X ,Y ,2)

#Fitting Polynomial with Degree 7 on our Dataset
p7_y_pred = fit_multidimensional_model(X ,Y ,7)

#Fitting Polynomial with Degree 10 on our Dataset
p10_y_pred = fit_multidimensional_model(X ,Y ,10)

#Fitting Polynomial with Degree 16 on our Dataset
p16_y_pred = fit_multidimensional_model(X ,Y ,16)
```

Concatenating our Predicted Y for each Degree into a single Multidimensional Array

In [32]:
```
#Initializing our Final Y_pred with degree 1 y_pred
y_pred = p1_y_pred

#Concatenating y_pred of Degree 2 to our Final Y_pred
y_pred = np.concatenate((y_pred ,p2_y_pred) ,axis = 1)

#Concatenating y_pred of Degree 7 to our Final Y_pred
y_pred = np.concatenate((y_pred ,p7_y_pred) ,axis = 1)

#Concatenating y_pred of Degree 10 to our Final Y_pred
y_pred = np.concatenate((y_pred ,p10_y_pred) ,axis = 1)

#Concatenating y_pred of Degree 16 to our Final Y_pred
y_pred = np.concatenate((y_pred ,p16_y_pred) ,axis = 1)
```

Plotting our Original Dataset and our Fitted Polynomial Linear Regression Model

In [33]:
```
#Initializing the text for the Figure Title
figure_title = 'Higher degree polynomial Fit on a Dataset'

#Creating the Subplot Title array by mapping a function to degree array
plot_titles = list(map(lambda x : 'Fitting Polynomial with Degree {} on the Dataset'

#Plotting the final Graph
plot_multdimensional_model(X ,Y ,y_pred ,figure_title ,plot_titles)
```



From the above graphs, we can see that as the degree of Polynomial increases, our model tries to overfit our dataset and as a result it will perform good on training dataset but bad on the unseen or Test dataset.In my perspective, the best model to fit our dataset is of degree 1 or degree 2

Task B: Effect of Regularization

Function to Fit Multidimensional Ridge Regression with Regularization and given degree on the dataset

In [34]:

```
def fit_multidimensional_model_regularized(X_train ,y_train ,degree ,lamda):
    #Creating the object of PolynomialFeatures with the provided degree
    p = PolynomialFeatures(degree = degree)

    #Fitting and Transforming our dataset into the multidimensional features
    data = p.fit_transform(X_train ,y_train)

    #Creating and Fitting a Ridge Regression model with L2 Regularization on our cre
    poly_reg = Ridge(alpha = lamda).fit(data ,y_train)

    #Calculating our Predicted Y using our Fitted Ridge regression Model
    y_pred = poly_reg.predict(data)

    #Returning our Predicted Y
    return y_pred
```

Fitting the Polynomial Ridge Regression with Degree = 10 and different values of λ on our Dataset

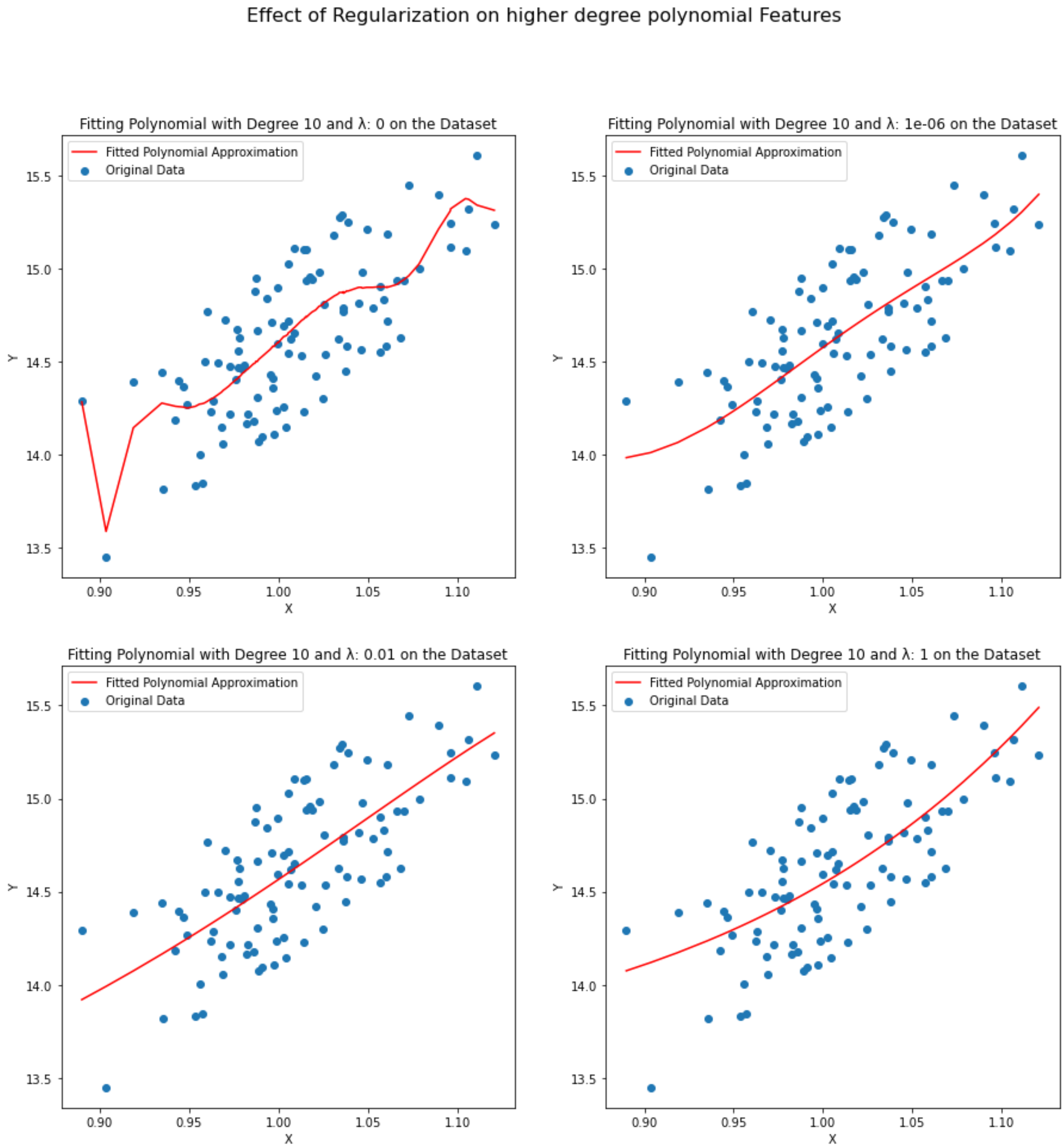
In [35]:
```
#Fitting Polynomial with Degree = 10 and λ = 0 on our Dataset
p0_y_pred = fit_multidimensional_model_regularized(X ,Y ,10 ,0)

#Fitting Polynomial with Degree = 10 and λ = 10^-6 on our Dataset
p6_y_pred = fit_multidimensional_model_regularized(X ,Y ,10 ,10**-6)

#Fitting Polynomial with Degree = 10 and λ = 10^-2 on our Dataset
p2_y_pred = fit_multidimensional_model_regularized(X ,Y ,10 ,10**-2)

#Fitting Polynomial with Degree = 10 and λ = 1 on our Dataset
p1_y_pred = fit_multidimensional_model_regularized(X ,Y ,10 ,1)
```

Concatenating our Predicted Y for each λ into a single Multidimensional Array

In [36]:
```
#Initializing our Final Y_pred with degree 10 and λ = 0 y_pred
y_pred = p0_y_pred

#Concatenating y_pred of Degree 10 and λ = 10^-6 to our Final Y_pred
y_pred = np.concatenate((y_pred ,p6_y_pred) ,axis = 1)

#Concatenating y_pred of Degree 10 and λ = 10^-2 to our Final Y_pred
y_pred = np.concatenate((y_pred ,p2_y_pred) ,axis = 1)

#Concatenating y_pred of Degree 10 and λ = 1 to our Final Y_pred
y_pred = np.concatenate((y_pred ,p1_y_pred) ,axis = 1)
```

Plotting our Original Dataset and our Fitted Polynomial Ridge Regression Model

In [37]:
```
#Initializing the text for the Figure Title
figure_title = 'Effect of Regularization on higher degree polynomial Features'

#Creating the Subplot Title array by mapping a function to Lambda λ array
plot_titles = list(map(lambda x : 'Fitting Polynomial with Degree 10 and λ: {} on th

#Plotting the final Graph
plot_multdimensional_model(X ,Y ,y_pred ,figure_title ,plot_titles)
```



Regularization is basically used to Penalize bad and extreme weights which are making our model overfit.In the above graphs, we are trying to fit a polynomial of degree 10 on our dataset and without regularization we can see it is overfitting our dataset. So we try with different values of λ on our polynomial with degree 10 and we can see it is making our model better by reducing the overfitting. In my Perspective the best λ to be used here are 10^-6 and 0.01

Exercise 3: Implementing Coordinate Descent

Splitting Wine Quality Dataset into X and Y matrix

In [38]:

```
#Appending a Bias Column in the starting of Wine Quality X matrix
wine_quality_X = np.append(np.ones(shape = (len(wine_quality_X) ,1)) ,wine_quality_X

#Reshaping the Wine Quality Y vector into a Column Vector
wine_quality_Y = wine_quality_Y.to_numpy().reshape(-1 ,1)
```

Splitting Wine Quality Matrix X and Y into Training and Test Sets

In [39]:

```
#Using the Sklearn train_test_split function to split my dataset into training and t
wine_X_train, wine_X_test, wine_y_train, wine_y_test = train_test_split(wine_quality
```

```
                                                                          shuffle = Tr
```

Implementation of Coordinate Descent

Function to return soft threshold value between two scalar values

In [40]:
```
def soft(x ,epsilon):
    if x > epsilon:
        return x - epsilon
    elif np.abs(x) <= epsilon:
        return 0
    elif x < -epsilon:
        return x + epsilon
```

Function to calculate the Gradient of the given Dataset

In [41]:
```
def calculate_g(X_train ,y_train ,beta ,m ,regularized ,lamda):
    #Removing the column m from the X train
    X_train_m = np.delete(X_train ,[m] ,axis = 1)

    #Converting the Beta vector into the Column Vector
    beta = beta.reshape(-1 ,1)

    #Extracting only the Column m from the X train
    xm = X_train[:,m]

    #If regularization is True than returning the regularized gradient with the regu
    if regularized:
        #Calculating the regularized term:
        # reg = 0.5 * λ / Xm.T * Xm
        regularized_term = (0.5 * lamda) / (np.dot(xm.T ,xm))

        #Returning the Soft Threshold value between gradient and regularized term
        return soft(np.dot(np.subtract(y_train,np.dot(X_train_m ,beta)).T ,xm)/np.do

    #If Regularization is False, then returning the simple Gradient
    return np.dot(np.subtract(y_train ,np.dot(X_train_m ,beta)).T ,xm)/np.dot(xm.T ,
```

Function to calculate the Loss value for the Coordinate Descent

In [42]:
```
def calculate_fbeta(X_train ,y_train ,beta ,regularized ,lamda):
    #Reshaping the beta vector into Column vector
    beta = beta.reshape(-1,1)

    #If regularization is True, then adding the regularized term in our Loss functio
    if regularized:
        #Returning the the regularized Loss value:
        # ƒ (Bˆ) = (y − XBˆ).T (y − XBˆ) + λ||B||1
        return np.dot(np.subtract(y_train ,np.dot(X_train ,beta)).T ,np.subtract(y_t

    #If regularization is False, then returning the simple Loss value:
    # ƒ (Bˆ) = (y − XBˆ).T (y − XBˆ)
    return np.dot(np.subtract(y_train ,np.dot(X_train ,beta)).T ,np.subtract(y_train
```

Function to Minimize the Coordinate Descent

In [43]:
```
def minimize_CD(X_train ,y_train ,beta ,alpha ,imax ,epsilon ,regularized ,lamda):
    #Creating a Multidimensional Array to store the history of Beta values
    beta_hist = np.zeros(shape=(len(beta) ,imax))

    #Iterating over all the iterations
```

```
    for i in range(1,imax):
        #Copying the previous Beta values to current Iteration beta values
        beta_hist[:,i] = beta_hist[:,i-1].copy()

        #Iterating over all the individual values of a single beta vector or every c
        for n in range(len(beta)):
            #Removing the nth element from the beta column vector
            beta_i = np.delete(beta_hist ,n ,axis=0)

            #Calculating the gradient without the nth element in the beta vector
            beta_hist[n,i] = calculate_g(X_train ,y_train ,beta_i[:,i] ,n ,regulariz

            #Checking the Stopping condition
            if calculate_fbeta(X_train ,y_train ,beta_hist[:,i-1] ,regularized ,lamd
                #Returning the all the beta history
                return np.delete(beta_hist ,np.arange(i+1,imax) ,axis = 1)

    #Returning the all the beta history
    return beta_hist
```

Function to fit the Linear Regression Model using the Coordinate Descent

In [44]:

```
def learn_linreg_CD(X_train ,y_train ,imax ,epsilon ,alpha ,regularized ,lamda):
    #Initializing a beta vector with zeros
    beta = np.zeros(shape=(len(X_train[0]) ,1))

    #Returning and Minimizing the Coordinate descent to find the optimal Beta vector
    return minimize_CD(X_train ,y_train ,beta ,alpha ,imax ,epsilon ,regularized ,la
```

Coordinate Descent Without Regularization

In [45]:

```
beta = learn_linreg_CD(wine_X_train ,wine_y_train ,1000 ,10**-10 ,0.001 ,False ,0)
```

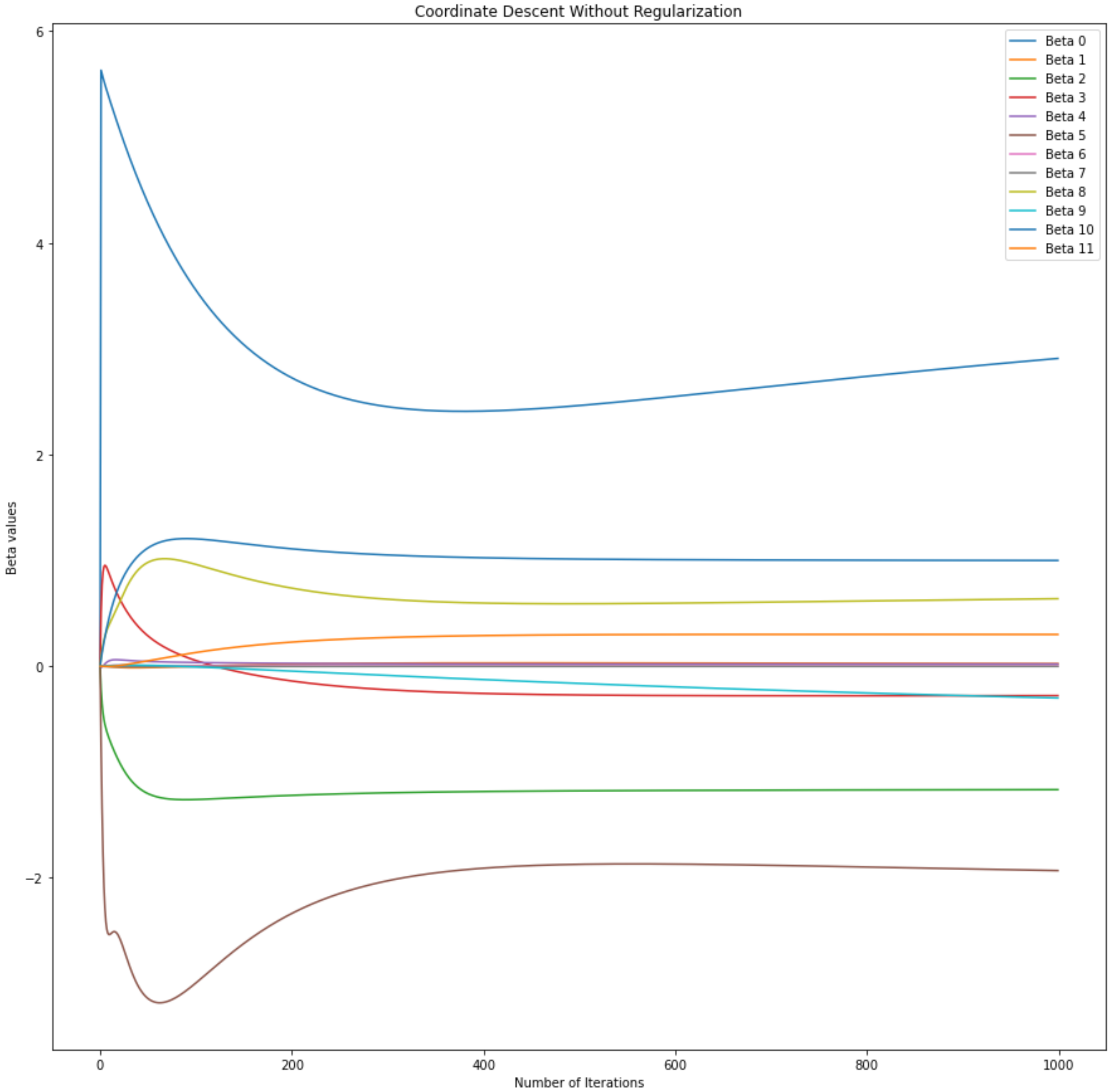
Plotting the Beta History without Regularization

In [46]:

```
#Creating a Figure with specific Size
fig = plt.figure(figsize=(15 ,15))

#Adding a Subplot
plt.subplot(111)

#For each beta vector, plotting it as a Line graph
for i in range(len(beta)):
    plt.plot([j for j in range(len(beta[0]))] ,beta[i,:] ,label = 'Beta {}'.format(i

#Setting some parameters for the graph
plt.xlabel('Number of Iterations')
plt.ylabel('Beta values')
plt.title('Coordinate Descent Without Regularization')
plt.legend(loc = 1)
```

Out[46]:

```
<matplotlib.legend.Legend at 0x18d5ec8eee0>
```



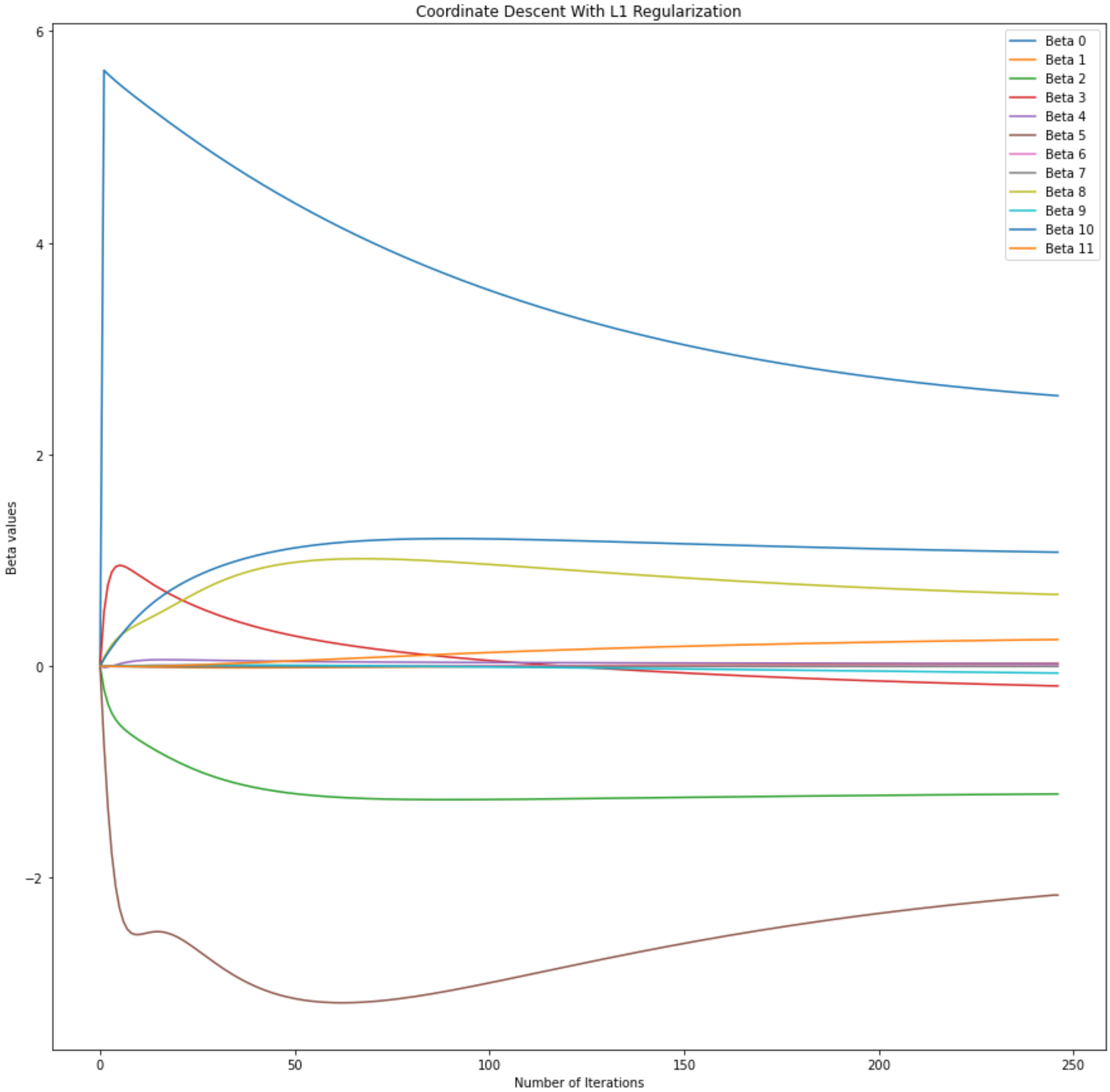
Coordinate Descent With Regularization

In [47]:
```
beta = learn_linreg_CD(wine_X_train ,wine_y_train ,1000 ,10**-2 ,0.001 ,True ,np.exp
```

Plotting the Beta History with Regularization

In [48]:
```
#Creating a Figure with specific Size
fig = plt.figure(figsize=(15 ,15))

#Adding a Subplot
plt.subplot(111)

#For each beta vector, plotting it as a Line graph
for i in range(len(beta)):
    plt.plot([j for j in range(len(beta[0]))] ,beta[i,:] ,label = 'Beta {}'.format(i

#Setting some parameters for the graph
plt.xlabel('Number of Iterations')
plt.ylabel('Beta values')
plt.title('Coordinate Descent With L1 Regularization')
plt.legend(loc = 1)
```

Out[48]: <matplotlib.legend.Legend at 0x18d5ed8b340>



Task C: Comparison

From the above graphs of Beta With and Without Regularization, we can infer following points: 1. The Graph without Regularization, shows that some beta's tends to go away from the median range and goes towards bigger values which as result can make our model overfit. 2. When we introduce Regularization in Beta calculation, all the beta values tends to come near the 0 mark to avoid Overfitting and also converges much faster as compared to Non-Regularized Version.