Lab Course Machine Learning

Exercise Sheet 6

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Exercise 0: Dataset Preprocessing

In [459…

```python
import numpy as np
import math
from sklearn.preprocessing import PolynomialFeatures
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import cm
from matplotlib.ticker import LinearLocator
from sympy import symbols, diff
import pandas as pd
import math
import warnings
import itertools
warnings.filterwarnings('ignore')
from sklearn import model_selection
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from math import sqrt
from sklearn.linear_model import SGDRegressor
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import StratifiedShuffleSplit
```

In [460…

```python
mu, sigma = 1, 0.05 # mean and standard deviation
X = np.random.normal(mu, sigma, size=(100, 1))
```

In [461…

```python
mu, sigma = 1, 0.1 # mean and standard deviation
r = np.random.normal(mu, sigma, size=(100, 1))
```

In [462…

```python
Y=1.3*(X**2) + (4.8*X) +8+r
```

(b)Wine Quality called D2:

In [9]:

```python
wq = pd.read_csv('winequality-red.csv',sep = ';')
```

In [10]:

```python
wq
```

Out[10]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4	5
1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	0.68	9.8	5
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	0.65	9.8	5
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	0.58	9.8	6
4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4	5
...	...	...	...	...	...	...	...	...	...	...	...	...
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10.5	5
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11.2	6
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	11.0	6
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10.2	5
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11.0	6

1599 rows × 12 columns

In [11]:

```python
is_NaN = wq.isnull()
row_has_NaN = is_NaN.any(axis=1)
rows_with_NaN = wq[row_has_NaN]
rows_with_NaN
```

Out[11]:

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

In [ ]:

In [12]:

```python
dsy = wq.loc[:, wq.columns != 'quality']
wqf = (dsy-dsy.mean())/dsy.std()
wqf
```

Out[12]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol
0	-0.528194	0.961576	-1.391037	-0.453077	-0.243630	-0.466047	-0.379014	0.558100	1.288240	-0.579025	-0.959946
1	-0.298454	1.966827	-1.391037	0.043403	0.223805	0.872365	0.624168	0.028252	-0.719708	0.128910	-0.584594
2	-0.298454	1.296660	-1.185699	-0.169374	0.096323	-0.083643	0.228975	0.134222	-0.331073	-0.048074	-0.584594
3	1.654339	-1.384011	1.483689	-0.453077	-0.264878	0.107558	0.411372	0.664069	-0.978798	-0.461036	-0.584594
4	-0.528194	0.961576	-1.391037	-0.453077	-0.243630	-0.466047	-0.379014	0.558100	1.288240	-0.579025	-0.959946
...	...	...	...	...	...	...	...	...	...	...	...
1594	-1.217415	0.403103	-0.980362	-0.382151	0.053829	1.541571	-0.075020	-0.978459	0.899605	-0.461036	0.072271
1595	-1.389721	0.123866	-0.877693	-0.240300	-0.541090	2.210777	0.137777	-0.861893	1.353012	0.600867	0.729136
1596	-1.159980	-0.099523	-0.723690	-0.169374	-0.243630	1.254769	-0.196617	-0.533387	0.705287	0.541872	0.541460
1597	-1.389721	0.654416	-0.775024	-0.382151	-0.264878	1.541571	-0.075020	-0.676446	1.676875	0.305894	-0.209243
1598	-1.332285	-1.216469	1.021680	0.752659	-0.434854	0.203159	-0.135818	-0.665849	0.510970	0.010921	0.541460

1599 rows × 11 columns

In [13]:

```python
wqf['quality'] = wq[['quality']]
wqf
```

Out[13]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	-0.528194	0.961576	-1.391037	-0.453077	-0.243630	-0.466047	-0.379014	0.558100	1.288240	-0.579025	-0.959946	5
1	-0.298454	1.966827	-1.391037	0.043403	0.223805	0.872365	0.624168	0.028252	-0.719708	0.128910	-0.584594	5
2	-0.298454	1.296660	-1.185699	-0.169374	0.096323	-0.083643	0.228975	0.134222	-0.331073	-0.048074	-0.584594	5
3	1.654339	-1.384011	1.483689	-0.453077	-0.264878	0.107558	0.411372	0.664069	-0.978798	-0.461036	-0.584594	6
4	-0.528194	0.961576	-1.391037	-0.453077	-0.243630	-0.466047	-0.379014	0.558100	1.288240	-0.579025	-0.959946	5
...	...	...	...	...	...	...	...	...	...	...	...	...
1594	-1.217415	0.403103	-0.980362	-0.382151	0.053829	1.541571	-0.075020	-0.978459	0.899605	-0.461036	0.072271	5
1595	-1.389721	0.123866	-0.877693	-0.240300	-0.541090	2.210777	0.137777	-0.861893	1.353012	0.600867	0.729136	6
1596	-1.159980	-0.099523	-0.723690	-0.169374	-0.243630	1.254769	-0.196617	-0.533387	0.705287	0.541872	0.541460	6
1597	-1.389721	0.654416	-0.775024	-0.382151	-0.264878	1.541571	-0.075020	-0.676446	1.676875	0.305894	-0.209243	5
1598	-1.332285	-1.216469	1.021680	0.752659	-0.434854	0.203159	-0.135818	-0.665849	0.510970	0.010921	0.541460	6

1599 rows × 12 columns

Exercise 1: Generalized Linear Models with Scikit Learn

Split your data into Train and Test Splits according to the 80%:20% ratio.

In [51]:

```python
wqf_train = wqf.loc[0:math.floor(len(wqf)*0.8)]
wqf_test = wqf.loc[math.floor(len(wqf)*0.8)+1:]
len(wqf) == len(wqf_train)+ len(wqf_test)
wqf_test
```

Out[51]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
1280	-0.700500	-0.378759	-0.364349	-0.453077	-0.222383	1.159168	0.228975	-0.607566	0.381425	-0.107068	-0.021567	6
1281	-0.700500	-0.378759	-0.364349	-0.453077	-0.222383	1.159168	0.228975	-0.607566	0.381425	-0.107068	-0.021567	6
1282	-0.241019	1.324583	-1.391037	-0.382151	-0.073654	-0.657248	-0.743808	-0.294955	0.122335	0.128910	0.447623	6
1283	0.218462	0.570645	0.046326	0.114328	0.181311	0.107558	0.684967	0.314370	-0.331073	-0.166063	-0.209243	6
1284	-0.757935	-0.602148	-0.415683	-0.169374	-0.349866	0.203159	-0.318215	-1.052638	0.510970	-0.579025	0.447623	5
...	...	...	...	...	...	...	...	...	...	...	...	...
1594	-1.217415	0.403103	-0.980362	-0.382151	0.053829	1.541571	-0.075020	-0.978459	0.899605	-0.461036	0.072271	5
1595	-1.389721	0.123866	-0.877693	-0.240300	-0.541090	2.210777	0.137777	-0.861893	1.353012	0.600867	0.729136	6
1596	-1.159980	-0.099523	-0.723690	-0.169374	-0.243630	1.254769	-0.196617	-0.533387	0.705287	0.541872	0.541460	6
1597	-1.389721	0.654416	-0.775024	-0.382151	-0.264878	1.541571	-0.075020	-0.676446	1.676875	0.305894	-0.209243	5
1598	-1.332285	-1.216469	1.021680	0.752659	-0.434854	0.203159	-0.135818	-0.665849	0.510970	0.010921	0.541460	6

319 rows × 12 columns

For each model, pick three sets of hyperparameters and learn each model

In [479…

```python
X_train = wqf_train.loc[:, wqf_train.columns != 'quality'].to_numpy()
Y_train = wqf_train[['quality']].to_numpy()

X_test = (wqf_test.loc[:, wqf_train.columns != 'quality']).to_numpy()
Y_test = (wqf_test[['quality']]).to_numpy()
```

In [480…

```python
n= 3
lamdaList =np.random.uniform(np.exp(-9),np.exp(-4),n)

numberofIterations = [250,500,1000]
hyperParamConfigs = []
for i in range (n):
    hyperParamConfigs.append([numberofIterations[i],lamdaList[i]])
```

In [481…

```python
hyperParamConfigs
```

Out[481…

```
[[250, 0.01304223276289804],
 [500, 0.010112096600584174],
 [1000, 0.017106943712182084]]
```

In [482…

```python
RMSE = []
for n,lamda in (hyperParamConfigs):
    # for ordinary least square alpha is 0
    ordinaryReg = SGDRegressor(alpha = 0,max_iter=n)
    ordinaryReg.fit(X_train,Y_train)
    pred_train_ordinaryReg= ordinaryReg.predict(X_train) #prediction
    rmseTrain_ordinaryReg = np.sqrt(mean_squared_error(Y_train,pred_train_ordinaryReg)) #RMSE

    pred_test_ordinaryReg= ordinaryReg.predict(X_test)
    rmseTest_ordinaryReg = np.sqrt(mean_squared_error(Y_test,pred_test_ordinaryReg))

    ridgeReg = SGDRegressor(alpha =lamda,max_iter=n,penalty='l2')
    ridgeReg.fit(X_train,Y_train)
    pred_train_ridgeReg= ridgeReg.predict(X_train)
    rmseTrain_ridgeReg = np.sqrt(mean_squared_error(Y_train,pred_train_ridgeReg))

    pred_test_ridgeReg= ridgeReg.predict(X_test)
    rmseTest_ridgeReg = np.sqrt(mean_squared_error(Y_test,pred_test_ridgeReg))

    lassoReg = SGDRegressor(alpha =lamda,max_iter=n,penalty='l1')
    lassoReg.fit(X_train,Y_train)
    pred_train_lassoReg= lassoReg.predict(X_train)
    rmseTrain_lassoReg = np.sqrt(mean_squared_error(Y_train,pred_train_lassoReg))

    pred_test_lassoReg= lassoReg.predict(X_test)
    rmseTest_lassoReg = np.sqrt(mean_squared_error(Y_test,pred_test_lassoReg))

    RMSE.append([n,lamda,rmseTrain_ordinaryReg,rmseTest_ordinaryReg,rmseTrain_ridgeReg,rmseTest_ridgeReg,rmseTr
```

In [483…

```python
Rmse = np.array(RMSE)
```

In [484…

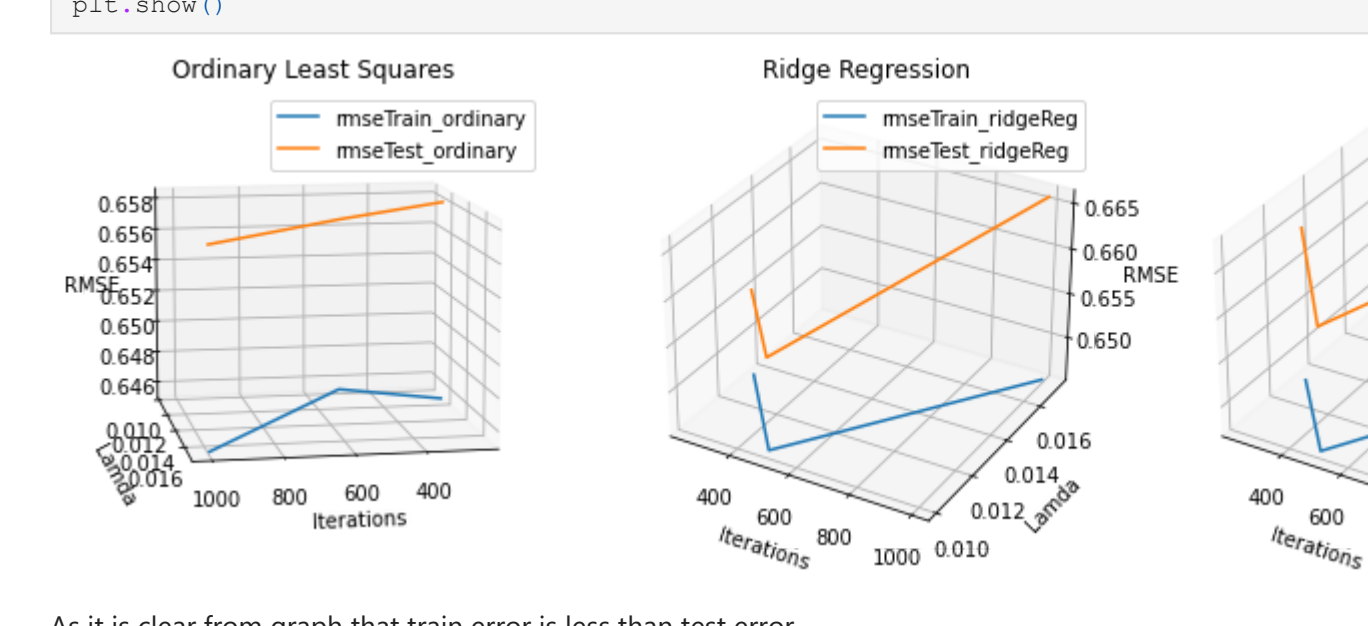
```python
np.array(hyperParamConfigs)[:,1]
```

Out[484…

```
array([0.01304223, 0.0101121 , 0.01710694])
```

In [508…

```python
fig = plt.figure(figsize=(14,10))

ax = fig.add_subplot(1, 3, 1, projection='3d')
ax.view_init(elev=10., azim=80.)
ax.plot(Rmse[:,0], Rmse[:,1], Rmse[:,2],label='rmseTrain_ordinary')
ax.plot(Rmse[:,0], Rmse[:,1], Rmse[:,3],label='rmseTest_ordinary')
ax.set_xlabel('Iterations')
ax.set_ylabel('Lamda')
ax.set_zlabel('RMSE')

ax.set_title("Ordinary Least Squares")
ax.legend()
ax = fig.add_subplot(1, 3, 2, projection='3d')
ax.plot(Rmse[:,0], Rmse[:,1], Rmse[:,4],label='rmseTrain_ridgeReg')
ax.plot(Rmse[:,0], Rmse[:,1], Rmse[:,5],label='rmseTest_ridgeReg')
ax.set_xlabel('Iterations')
ax.set_ylabel('Lamda')
ax.set_zlabel('RMSE')
ax.set_title('Ridge Regression')
ax.legend()
ax = fig.add_subplot(1, 3, 3, projection='3d')
ax.plot(Rmse[:,0], Rmse[:,1], Rmse[:,6],label='rmseTrain_lassoReg')
ax.plot(Rmse[:,0], Rmse[:,1], Rmse[:,7],label='rmseTest_lassoReg')
ax.set_xlabel('Iterations')
ax.set_ylabel('Lamda')
ax.set_zlabel('RMSE')
ax.set_title('LASSO')
ax.legend()
plt.show()
```



As it is clear from graph that train error is less than test error

3. Now tune the hyperparameters using scikit learn GridSearchCV

In [635…

```python
def get_best_params(train_x, train_y,alphaRange,iterationRange,penalty):
    param_grid = dict(alpha=alphaRange, max_iter=iterationRange)

    cv = StratifiedShuffleSplit(n_splits=2, test_size=0.2, random_state=42) # stratifying sample for crossvalic
    # for param grid calling GridSearchCV with penalty(for specifying model) and diff hyper params in grid
    grid = GridSearchCV(SGDRegressor(penalty=penalty), param_grid=param_grid, cv=cv,return_train_score=True, n_
    grid.fit(train_x, train_y)

    print("The best parameters are %s with a score of %0.2f" % (grid.best_params_, grid.best_score_))

    scores = []
    # to calculate test and train score for each setting in parameter and adding it to scores list
    for i,j,k in zip (grid.cv_results_['params'],grid.cv_results_['mean_test_score'],grid.cv_results_['mean_tra
        scores.append([j,k,i['alpha'],i['max_iter']])
    no_iteration_best = grid.best_params_['max_iter']
    alpha_best = grid.best_params_['alpha']

    sgd = SGDRegressor(alpha =alpha_best,max_iter=no_iteration_best,penalty=penalty)

    return sgd,np.array(scores),no_iteration_best,alpha_best
```

In [638…

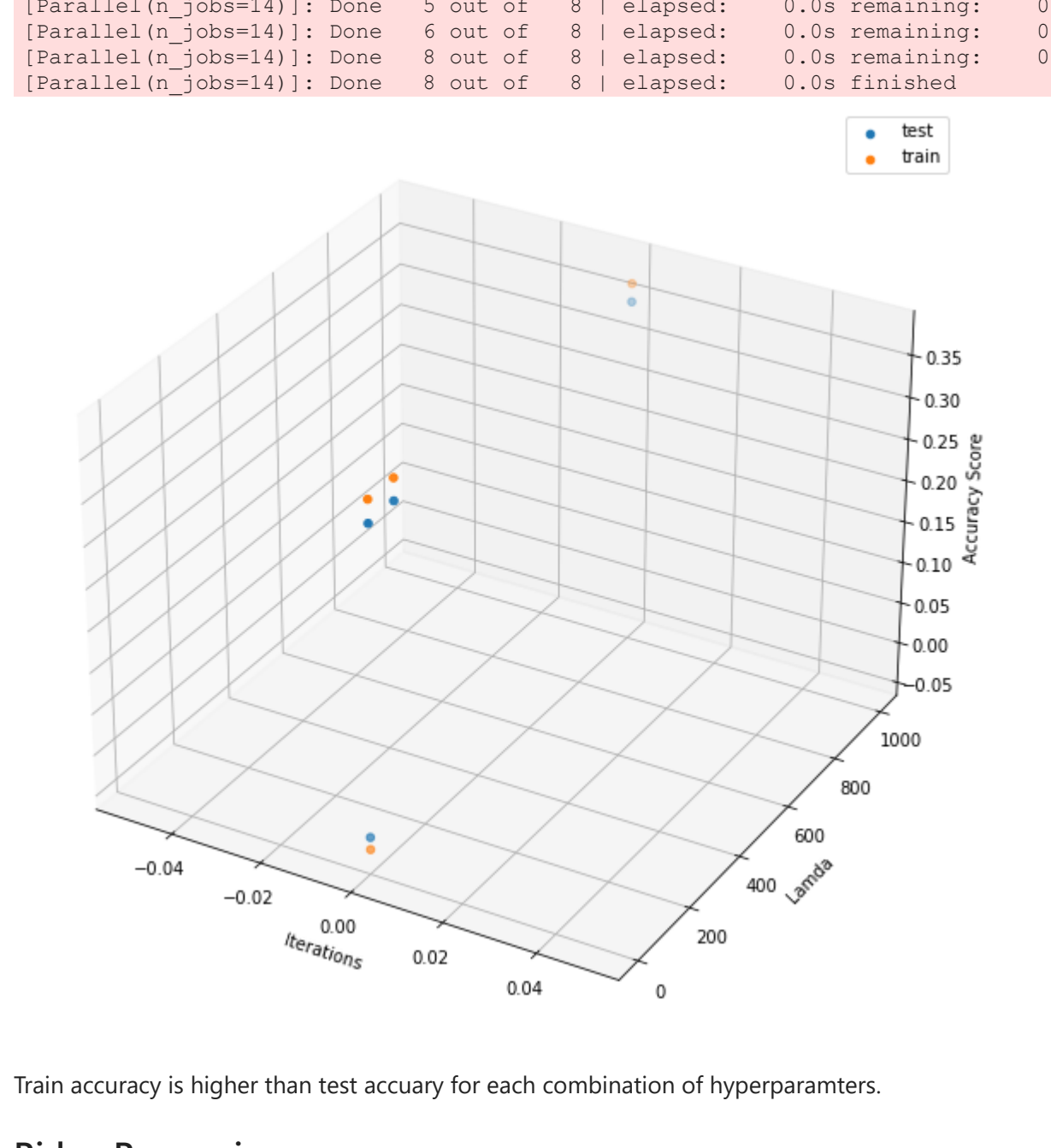
```python
X_train = wqf_train.loc[:, wqf_train.columns != 'quality'].to_numpy()
Y_train = wqf_train[['quality']].to_numpy()

X_test = (wqf_test.loc[:, wqf_train.columns != 'quality']).to_numpy()
Y_test = (wqf_test[['quality']]).to_numpy()
```

Ordinary Least Squares

In [639…

```python
iterationRange = [1, 10, 100, 1000]
alphaRange =[0]
orginarySGD,scores,no_iteration_best_ord,alpha_best_ord = get_best_params(X_train, Y_train,alphaRange,iteration
fig = plt.figure(figsize=(14,10))
ax = fig.add_subplot(1, 1, 1, projection='3d')
ax.scatter(scores[:,2], scores[:,3], scores[:,0],label='test')
ax.scatter(scores[:,2], scores[:,3], scores[:,1],label='train')
ax.set_xlabel('Iterations')
ax.set_ylabel('Lamda')
ax.set_zlabel('Accuracy Score')
ax.legend()
plt.show()
```

```
Fitting 2 folds for each of 4 candidates, totalling 8 fits
The best parameters are {'alpha': 0, 'max_iter': 1000} with a score of 0.35
[Parallel(n_jobs=14)]: Using backend LokyBackend with 14 concurrent workers.
[Parallel(n_jobs=14)]: Batch computation too fast (0.0040s.) Setting batch_size=2.
[Parallel(n_jobs=14)]: Done   2 out of   8 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=14)]: Done   3 out of   8 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=14)]: Done   4 out of   8 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=14)]: Done   5 out of   8 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=14)]: Done   6 out of   8 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=14)]: Done   8 out of   8 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=14)]: Done   8 out of   8 | elapsed:    0.0s finished
```



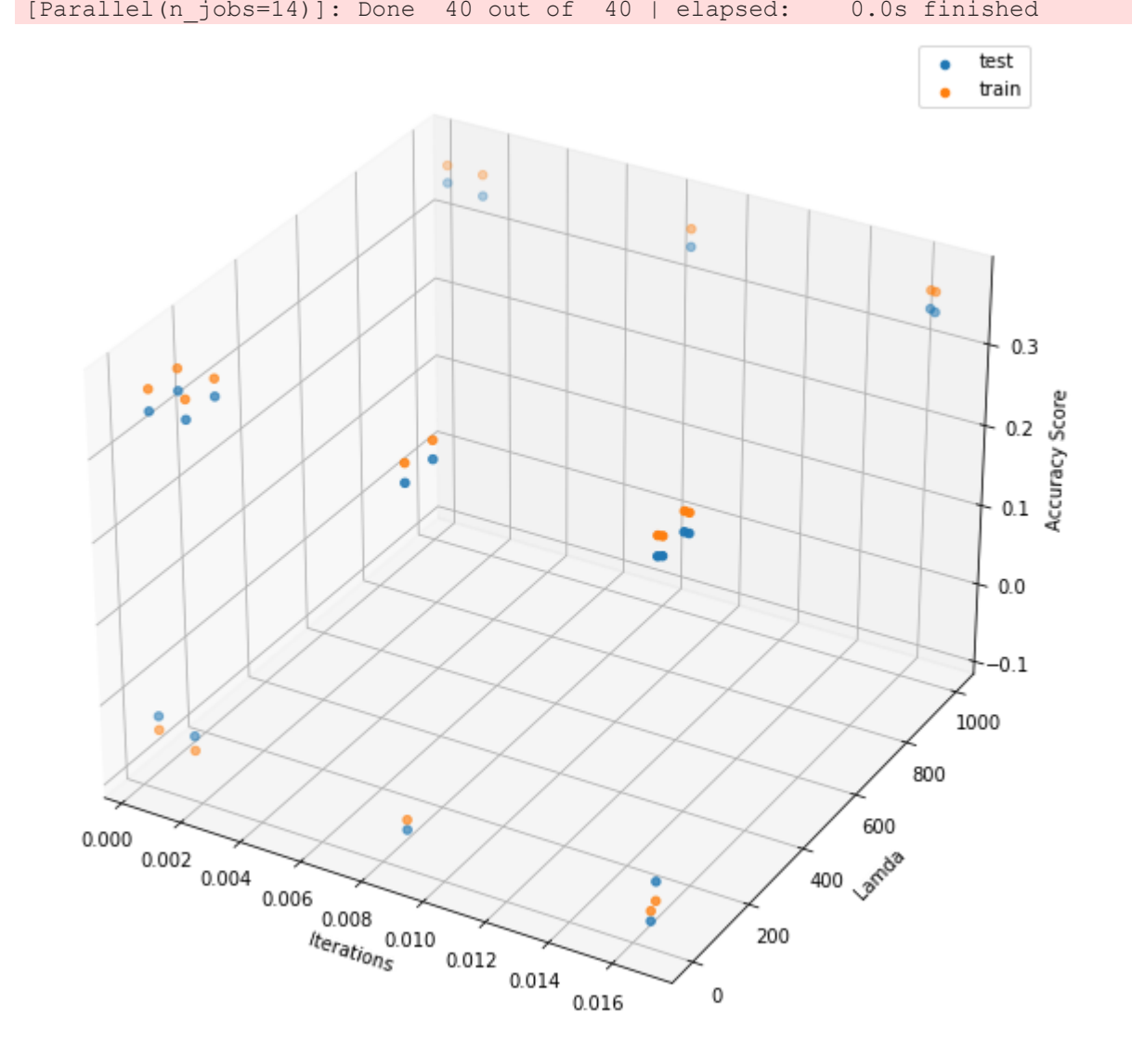
Train accuracy is higher than test accuary for each combination of hyperparamters.

Ridge Regression

In [640…

```python
n= 5
iterationRange = [1, 10, 100, 1000]
alphaRange = np.random.uniform(np.exp(-9),np.exp(-4),n)
ridgeSGD,scores,no_iteration_best_rig,alpha_best_rig = get_best_params(X_train, Y_train,alphaRange,iterationRar
fig = plt.figure(figsize=(14,10))

ax = fig.add_subplot(1, 1, 1, projection='3d')
ax.scatter(scores[:,2], scores[:,3], scores[:,0],label='test')
ax.scatter(scores[:,2], scores[:,3], scores[:,1],label='train')
ax.set_xlabel('Iterations')
ax.set_ylabel('Lamda')
ax.set_zlabel('Accuracy Score')
ax.legend()
plt.show()
```

```
Fitting 2 folds for each of 20 candidates, totalling 40 fits
The best parameters are {'alpha': 0.0005878382651812713, 'max_iter': 1000} with a score of 0.35
[Parallel(n_jobs=14)]: Using backend LokyBackend with 14 concurrent workers.
[Parallel(n_jobs=14)]: Batch computation too fast (0.0100s.) Setting batch_size=2.
[Parallel(n_jobs=14)]: Done   4 tasks      | elapsed:    0.0s
[Parallel(n_jobs=14)]: Done  13 tasks      | elapsed:    0.0s
[Parallel(n_jobs=14)]: Done  18 out of  40 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=14)]: Done  23 out of  40 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=14)]: Done  28 out of  40 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=14)]: Done  33 out of  40 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=14)]: Done  38 out of  40 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=14)]: Done  40 out of  40 | elapsed:    0.0s finished
```



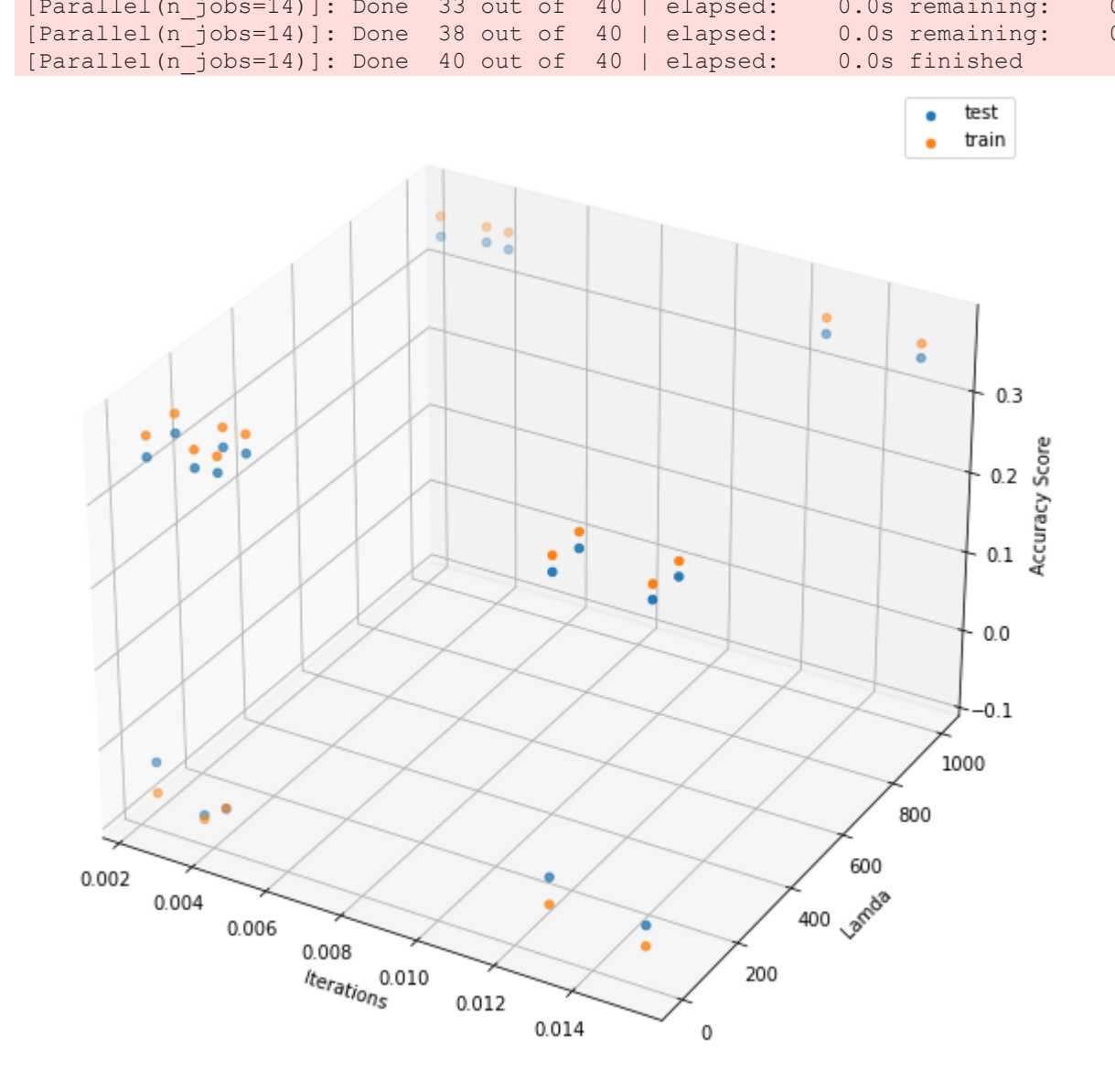
LASSO

Train accuracy is higher than test accuary for each combination of hyperparamters.

In [641…

```python
n= 5
iterationRange = [1, 10, 100, 1000]
alphaRange = np.random.uniform(np.exp(-9),np.exp(-4),n)
lassoSGD,scores,no_iteration_best_las,alpha_best_las = get_best_params(X_train, Y_train,alphaRange,iterationRar
fig = plt.figure(figsize=(14,10))
ax = fig.add_subplot(1, 1, 1, projection='3d')
ax.scatter(scores[:,2], scores[:,3], scores[:,0],label='test')
ax.scatter(scores[:,2], scores[:,3], scores[:,1],label='train')
ax.set_xlabel('Iterations')
ax.set_ylabel('Lamda')
ax.set_zlabel('Accuracy Score')
ax.legend()
plt.show()
```

```
Fitting 2 folds for each of 20 candidates, totalling 40 fits
The best parameters are {'alpha': 0.0037581469970294854, 'max_iter': 1000} with a score of 0.35
[Parallel(n_jobs=14)]: Using backend LokyBackend with 14 concurrent workers.
[Parallel(n_jobs=14)]: Batch computation too fast (0.0110s.) Setting batch_size=2.
[Parallel(n_jobs=14)]: Done   4 tasks      | elapsed:    0.0s
[Parallel(n_jobs=14)]: Done  13 tasks      | elapsed:    0.0s
[Parallel(n_jobs=14)]: Done  18 out of  40 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=14)]: Done  23 out of  40 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=14)]: Done  28 out of  40 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=14)]: Done  33 out of  40 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=14)]: Done  38 out of  40 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=14)]: Done  40 out of  40 | elapsed:    0.0s finished
```



Train accuracy is higher than test accuary for each combination of hyperparamters.

Using the optimal hyperparameter you have to evaluate each model on the Test Set.

In [647…

```python
RMSE = []
ordinaryReg = SGDRegressor(alpha = alpha_best_ord,max_iter=no_iteration_best_ord)
ordinaryReg.fit(X_train,Y_train)
pred_train_ordinaryReg= ordinaryReg.predict(X_train)
rmseTrain_ordinaryReg = np.sqrt(mean_squared_error(Y_train,pred_train_ordinaryReg))

pred_test_ordinaryReg= ordinaryReg.predict(X_test)
rmseTest_ordinaryReg = np.sqrt(mean_squared_error(Y_test,pred_test_ordinaryReg))

ridgeReg = SGDRegressor(alpha =alpha_best_rig,max_iter=no_iteration_best_rig,penalty='l2')
ridgeReg.fit(X_train,Y_train)
pred_train_ridgeReg= ridgeReg.predict(X_train)
rmseTrain_ridgeReg = np.sqrt(mean_squared_error(Y_train,pred_train_ridgeReg))

pred_test_ridgeReg= ridgeReg.predict(X_test)
rmseTest_ridgeReg = np.sqrt(mean_squared_error(Y_test,pred_test_ridgeReg))

lassoReg = SGDRegressor(alpha =alpha_best_las,max_iter=no_iteration_best_las,penalty='l1')
lassoReg.fit(X_train,Y_train)
pred_train_lassoReg= lassoReg.predict(X_train)
rmseTrain_lassoReg = np.sqrt(mean_squared_error(Y_train,pred_train_lassoReg))

pred_test_lassoReg= lassoReg.predict(X_test)
rmseTest_lassoReg = np.sqrt(mean_squared_error(Y_test,pred_test_lassoReg))
RMSE.append([n,lamda,rmseTrain_ordinaryReg,rmseTest_ordinaryReg,rmseTrain_ridgeReg,rmseTest_ridgeReg,rmseTrain_
```

In [644…

```python
print('Ordinary Least Squares: Train Rmse:',rmseTrain_ordinaryReg,',Test Rmse:',rmseTest_ordinaryReg,', Alpha E
```

```
Ordinary Least Squares: Train Rmse: 0.6451959565143569 ,Test Rmse: 0.6591434487027781 , Alpha Best: 0 , Best No
of iterations: 1000
```

In [645…

```python
print('Ridge Regression :',rmseTrain_ridgeReg,',Test Rmse:',rmseTest_ridgeReg,', Alpha Best:',alpha_best_rig,',
```

```
Ridge Regression : 0.6455985682230949 ,Test Rmse: 0.6576323366994828 , Alpha Best: 0.0005878382651812713 , Best
No of iterations: 1000
```

In [646…

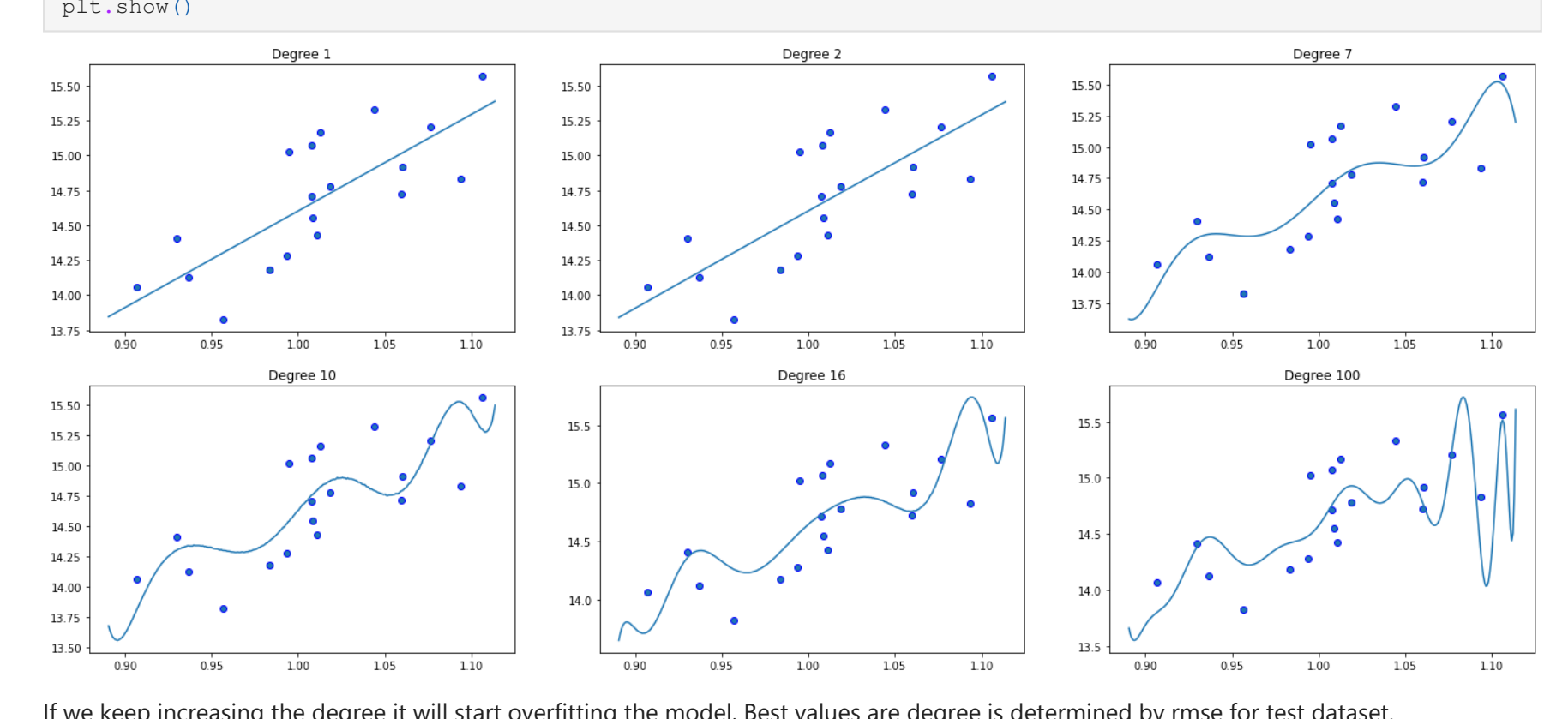
```python
print('LASSO :',rmseTrain_lassoReg,',Test Rmse:',rmseTest_lassoReg,', Alpha Best:',alpha_best_las,', Best No of
```

```
LASSO : 0.6451102978427398 ,Test Rmse: 0.6576034561282299 , Alpha Best: 0.0037581469970294854 , Best No of iter
ations: 1000
```

Exercise 2: Higher Order Polynomial Regression

In [648…

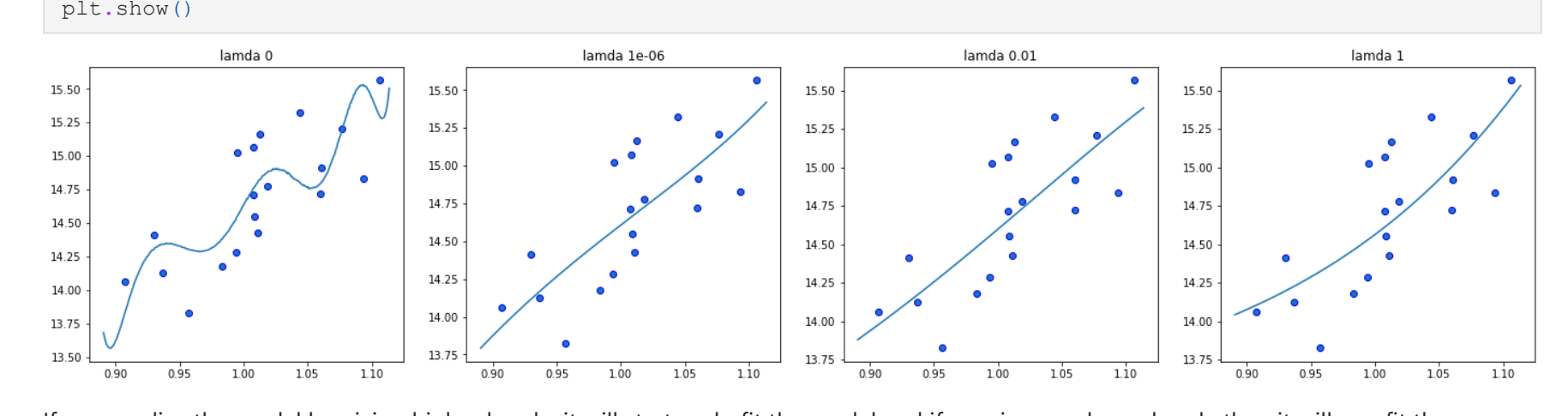
```python
np.random.seed(3116)
mu, sigma = 1, 0.05 # mean and standard deviation
X = np.random.normal(mu, sigma, size=(100, 1))
mu, sigma = 1, 0.1 # mean and standard deviation
r = np.random.rand(100,1)
Y=1.3*(X**2) + (4.8*X) +8+r
degrees = [1,2,7, 10, 16 , 100]
plt.figure(figsize=(24, 10))
for i in range(len(degrees)):
    ax = plt.subplot(2, len(degrees)/2, i + 1)
    #transforming X into polynommial
    polynomial_features = PolynomialFeatures(degree=degrees[i], include_bias=False)
    linear_regression = LinearRegression()
    pipeline = Pipeline(
        [
            ("polynomial_features", polynomial_features),
            ("linear_regression", linear_regression),
        ]
    )

    X_seq = np.linspace(X.min(),X.max(),300).reshape(-1,1)

    X_train =X[0:math.floor(len(X)*0.8),:]
    X_test =X[math.floor(len(X)*0.8)+1:,:]

    y_train = Y[0:math.floor(len(Y)*0.8),:]
    y_test =Y[math.floor(len(Y)*0.8)+1:,:]
    pipeline.fit(X_train, y_train)
    regr = linear_model.LinearRegression()
    regr.fit(X_fit_train, y_train)
    y_pred_test = pipeline.predict(X_test)


    plt.plot(X_seq,pipeline.predict(X_seq), label="Model")
    plt.scatter(X_test, y_test, edgecolor="b", label="Samples")
    plt.title(
        "Degree {}".format(
            degrees[i]
        )
    )
plt.show()
```



If we keep increasing the degree it will start overfitting the model, Best values are degree is determined by rmse for test dataset.

In [649…

```python
lamda = [0,10**(-6),10**(-2),1]
plt.figure(figsize=(24, 5))
for i in range(len(lamda)):
    ax = plt.subplot(1, len(lamda), i + 1)
    polynomial_features = PolynomialFeatures(degree=10, include_bias=False)
    linear_regression = Ridge(alpha=lamda[i])
    pipeline = Pipeline(
        [
            ("polynomial_features", polynomial_features),
            ("linear_regression", linear_regression),
        ]
    )

    X_seq = np.linspace(X.min(),X.max(),300).reshape(-1,1)

    X_train =X[0:math.floor(len(X)*0.8),:]
    X_test =X[math.floor(len(X)*0.8)+1:,:]

    y_train = Y[0:math.floor(len(Y)*0.8),:]
    y_test =Y[math.floor(len(Y)*0.8)+1:,:]
    pipeline.fit(X_train, y_train)
    regr = linear_model.LinearRegression()
    regr.fit(X_fit_train, y_train)
    y_pred_test = pipeline.predict(X_test)


    plt.plot(X_seq,pipeline.predict(X_seq), label="Model")
    plt.scatter(X_test, y_test, edgecolor="b", label="Samples")
    plt.title(
        "lamda {}".format(
            lamda[i]
        )
    )
plt.show()
```



If we penalize the model by giving higher lamda, it will start underfit the model and if we give very lower lamda than it will overfit the model.So to create a balance we have to give moderate values for lamda.

Exercise 3: Implementing Coordinate Descent

In [686…

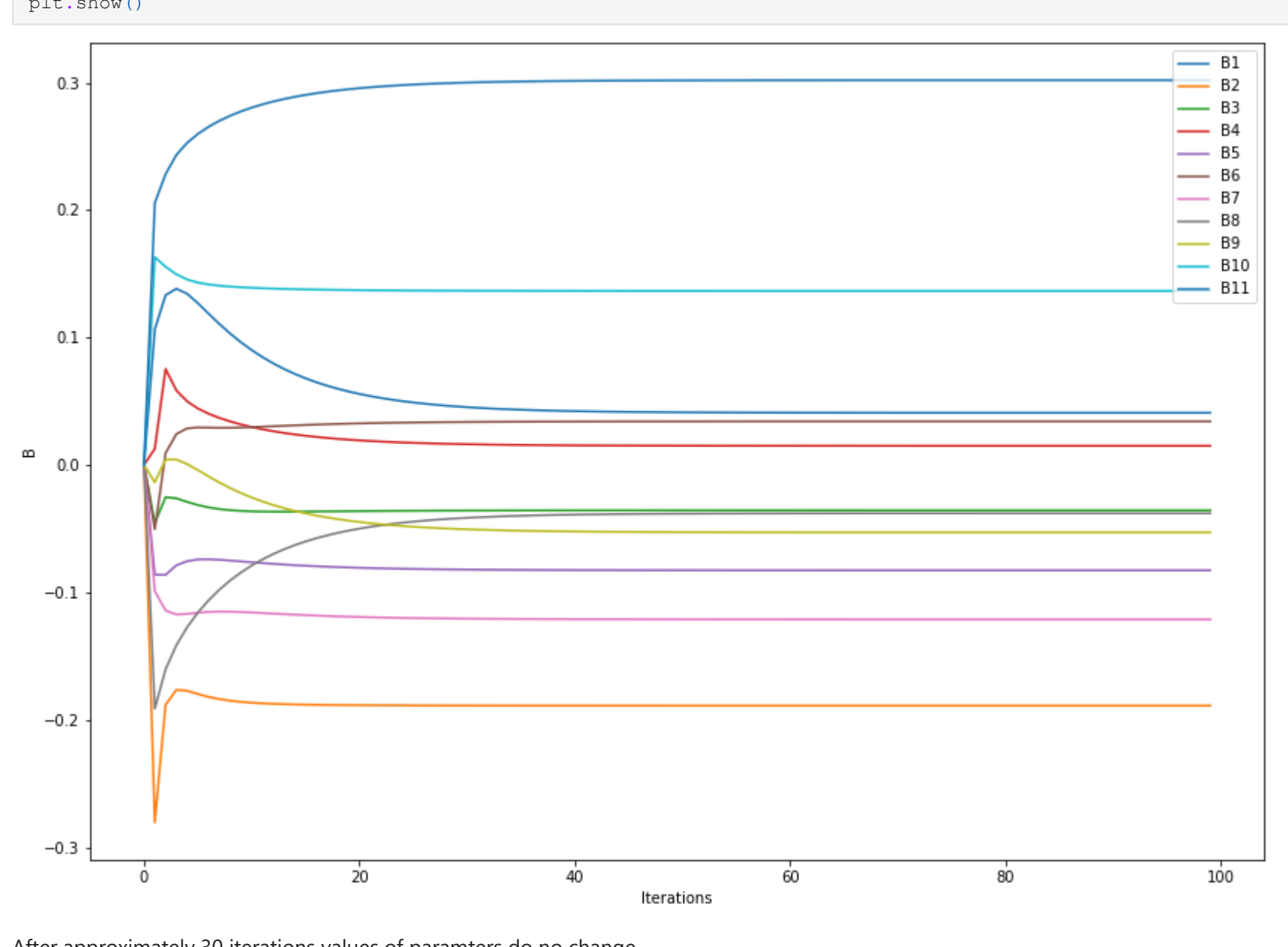
```python
def loss(X,Y,B):
    sum = 0
    for i in range (len(X)):
        sum  = sum +((Y[i].T-np.dot(X[i],B)) ** 2)
    return sum
def cordinateDecent(X,Y,B,imax):
    f = loss(X,Y,B)

    BList = []
    for i in range (imax):
        BList.append(list(B))

        for m in range (len(B)):
            X_minus_m = np.delete(X, m, axis=1)
            B_minus_m = np.delete(B, m, axis=0).reshape(-1,1)
            g = np.dot(np.subtract(Y,np.dot(X_minus_m,B_minus_m)).T,X[:,m])/np.dot(X[:,m].T,X[:,m])
            B[m] = g


    return np.array(BList)
```

In [700…

```python
X_train = wqf_train.loc[:, wqf_train.columns != 'quality']
Y_train = wqf_train[['quality']]
X_test = (wqf_test.loc[:, wqf_test.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 = (wqf_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]))
bList = cordinateDecent(X,Y,B,100)
```

In [701…

```python
fig = plt.figure(figsize=(14,10))
ax = plt.axes()


for i in range(1,len(B)):
    ax.plot(bList[:,i],label='B'+str(i))

ax.set_xlabel('Iterations')
ax.set_ylabel('B')
ax.legend()
plt.show()
```



After approximately 30 iterations values of paramters do no change.

In [702…

```python
def cordinateDecentLI(X,Y,B,imax,lamda):
    f = loss(X,Y,B)

    BList = []
    for i in range (imax):
        BList.append(list(B))
        for m in range (len(B)):
            X_minus_m = np.delete(X, m, axis=1)
            B_minus_m = np.delete(B, m, axis=0).reshape(-1,1)
            e = (0.5*lamda)/np.dot(X[:,m].T,X[:,m])
            g = np.dot((Y-np.dot(X_minus_m,B_minus_m)).T,X[:,m])/np.dot(X[:,m].T,X[:,m])

            if(g>e):
                B[m] = g-e
            elif(abs(g)<=e):
                B[m] = 0
            elif(g<-e):
                B[m] = g+e

    return np.array(BList)
```

In [703…

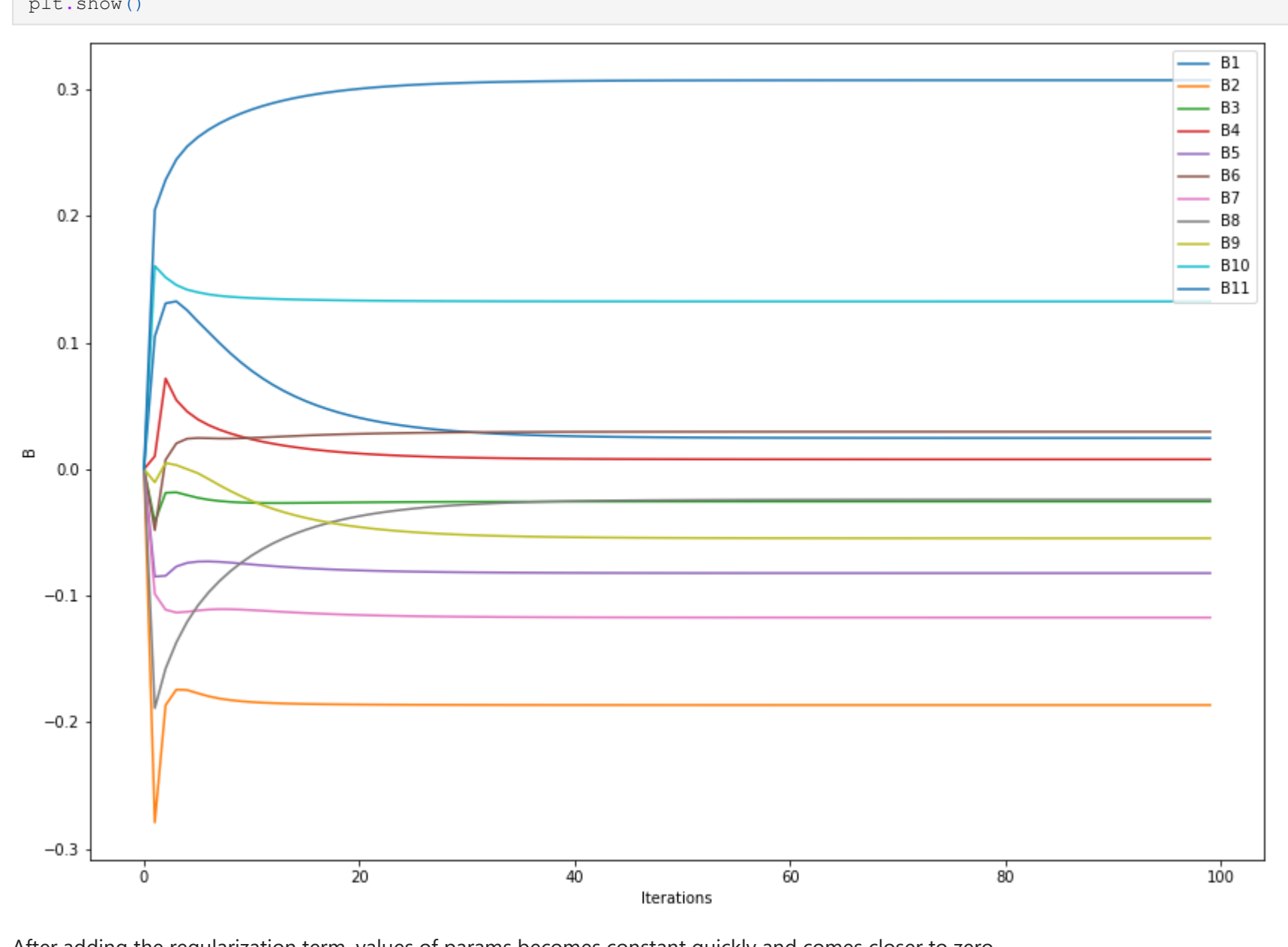
```python
B = np.zeros(len(X[0]))
bList = cordinateDecentLI(X,Y,B,100,5)
bList
```

Out[703…

```
array([[ 0.00000000e+00,  0.00000000e+00,  0.00000000e+00, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00],
       [ 5.66289063e+00,  1.04866299e-01, -2.79133368e-01, ...,
        -1.04023378e-02,  1.60508117e-01,  2.04881699e-01],
       [ 5.65951307e+00,  1.31018790e-01, -1.86496158e-01, ...,
         4.86667965e-03,  1.51496515e-01,  2.28524425e-01],
       ...,
       [ 5.65806269e+00,  2.45998920e-02, -1.86363721e-01, ...,
        -5.45829717e-02,  1.32472280e-01,  3.07277691e-01],
       [ 5.65806269e+00,  2.45997266e-02, -1.86363725e-01, ...,
        -5.45830628e-02,  1.32472272e-01,  3.07277761e-01],
       [ 5.65806270e+00,  2.45995800e-02, -1.86363729e-01, ...,
        -5.45831435e-02,  1.32472266e-01,  3.07277823e-01]])
```

In [704…

```python
fig = plt.figure(figsize=(14,10))
ax = plt.axes()


for i in range(1,len(B)):
    ax.plot(bList[:,i],label='B'+str(i))

ax.set_xlabel('Iterations')
ax.set_ylabel('B')
ax.legend()
plt.show()
```



After adding the regularization term, values of params becomes constant quickly and comes closer to zero.

In [ ]: