Shaikat_303527_lab_5_Q2

November 26, 2019

1 Preprocessing bank marketing dataset

In [1]:
```
import pandas as pd
import sys
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
pd.options.mode.chained_assignment = None
from sklearn.model_selection import train_test_split

filename = r"E:\Documents\University of Hildesheim\Machine learning lab\lab5\bank.csv"
bank = pd.read_csv(filename,delimiter=';')
```

In [2]:
```
bank.dropna(inplace=True)
```

In [3]:
```
col=['job','marital','education','default','housing','loan','month','contact','duratio
bank[col] = bank[col].astype('category')
```

In [4]:
```
bank_enc = bank.apply(lambda x: x.cat.codes if x.dtype.name == 'category' else x)
```

In [5]:
```
Ydata_bank = bank_enc['y']
Xdata_bank = bank_enc.loc[:,bank_enc.columns!='y']
Xdata_bank = (Xdata_bank - Xdata_bank.mean())/Xdata_bank.std() #data normalized

x_train_bank, x_test_bank, y_train_bank, y_test_bank =train_test_split(Xdata_bank,
                                                                        Ydata_bank,trai
                                                                        test_size=0.2,
                                                                        random_state=0)
```

In [6]:
```
y_train_bank=pd.DataFrame(y_train_bank.values.reshape(-1,1))
y_test_bank=pd.DataFrame(y_test_bank.values.reshape(-1,1))
x_train_bank=pd.DataFrame(x_train_bank.values)
x_test_bank=pd.DataFrame(x_test_bank.values)
```

In [23]:
```
print('x_train_bank :',x_train_bank.shape)
print('x_test_bank :',x_test_bank.shape)
print('y_train_bank :',y_train_bank.shape)
print('y_test_bank :',y_test_bank.shape)
```

```
x_train_bank : (3616, 16)
x_test_bank : (905, 16)
y_train_bank : (3616, 1)
y_test_bank : (905, 1)
```

In [10]:
```python
x_train_bank.shape
```

Out[10]:
```
(3616, 16)
```

In [11]:
```python
def logistic_function(X, beta):
    z = np.dot(X,beta)
    return 1 / (1 + np.exp(-z))

def log_likelihood(x, y, beta):
    z = np.dot(x, beta)
    log = np.sum( y*z - np.log(1 + np.exp(z)) )
    return log

betas = lambda x,y,beta,alpha,lamda : beta-alpha*(-2*np.dot(x.T,y-logistic_function(x
rmse  = lambda y,ypred: np.sqrt(np.mean((y-ypred)**2))
cost  = lambda y,ypred: np.mean((y - ypred)**2)
```

In [83]:
```python
def stochastic_gradient_descent(x_train,y_train,alpha,epochs,lamda,x_test,y_test):
#     print('x_train_bank :',x_train.shape)
#     print('x_test_bank :',x_test.shape)
#     print('y_train_bank :',y_train.shape)
#     print('y_test_bank :',y_test.shape)

    m_train,n_features = np.shape(x_train)
    ini_alpha          = alpha
    beta_hat           = np.random.random(n_features).reshape(-1,1)
    rmsetrain          = []
    rmsetest           = []
    y_hat              = logistic_function(x_train,beta_hat)

    chunk_size = 50
    for i in range(epochs):
        for chunk in range(len(x_train)//chunk_size):
            x_chunk  = x_train[chunk*chunk_size:min((chunk+1)*chunk_size,len(x_train))
            y_chunk  = y_train[chunk*chunk_size:min((chunk+1)*chunk_size,len(y_train))

            beta_hat = betas(x_chunk,y_chunk,beta_hat,alpha,lamda)

        y_hat=logistic_function(x_train,beta_hat)

        rmsetest.append(rmse(y_test,logistic_function(x_test,beta_hat)))
        rmsetrain.append(rmse(y_train,logistic_function(x_train,beta_hat)))
    return rmsetest,rmsetrain
```

2 Hypertuning parameters tuning

2.0.1 The function gridsearch is used to create the combinations of alpha and lamda

2.0.2 The function data_k_divide is used to divide the dataset according to the number of k fold

2.0.3 The function k_data_train_test is used to get random test and train data in every kfold

In [84]:
```
import math as Math

def gridsearch(alpha,lamda):
    comb=[]
    for i in range(0,len(alpha)):
        for k in range(0,len(lamda)):
            comb.append(dict([('alpha',alpha[i]),('lamda',lamda[k])]))
    return comb

def data_k_divide(data,k):
    k_size=Math.floor(len(data)/k)
    k_data=[]
    c=0
    for i in range (0,k):
        data_set=pd.DataFrame(data.head(0))
        for j in range(i*k_size,(i*k_size)+k_size):
            data_set=data_set.append(data.iloc[j])
            c=c+1
        k_data.append(data_set)

    #adding datas which are remaining at the end of k division
    for j in range(c,len(data)):
        k_data[k-1]=k_data[k-1].append(data.iloc[j])
    return k_data

def k_data_train_test(x,y,k):
    k_folded_data=[]
    for i in range(0,k):
        x_test=x[i]
        y_test=y[i]
        x_train=pd.DataFrame()
        y_train=pd.DataFrame()
        for j in range(0,k):
            if i!=j:
                x_train=x_train.append(x[j])
                y_train=y_train.append(y[j])
        final_data=dict([('x',x_train),('y',y_train),('xt',x_test),('yt',y_test)])
        k_folded_data.append(final_data)
    return k_folded_data
```

```
def kfold(x_train,y_train,k,x_test,y_test):
    x_train_k=data_k_divide(x_train,k)
    y_train_k=data_k_divide(y_train,k)
    data=k_data_train_test(x_train_k,y_train_k,k)
    return data
```

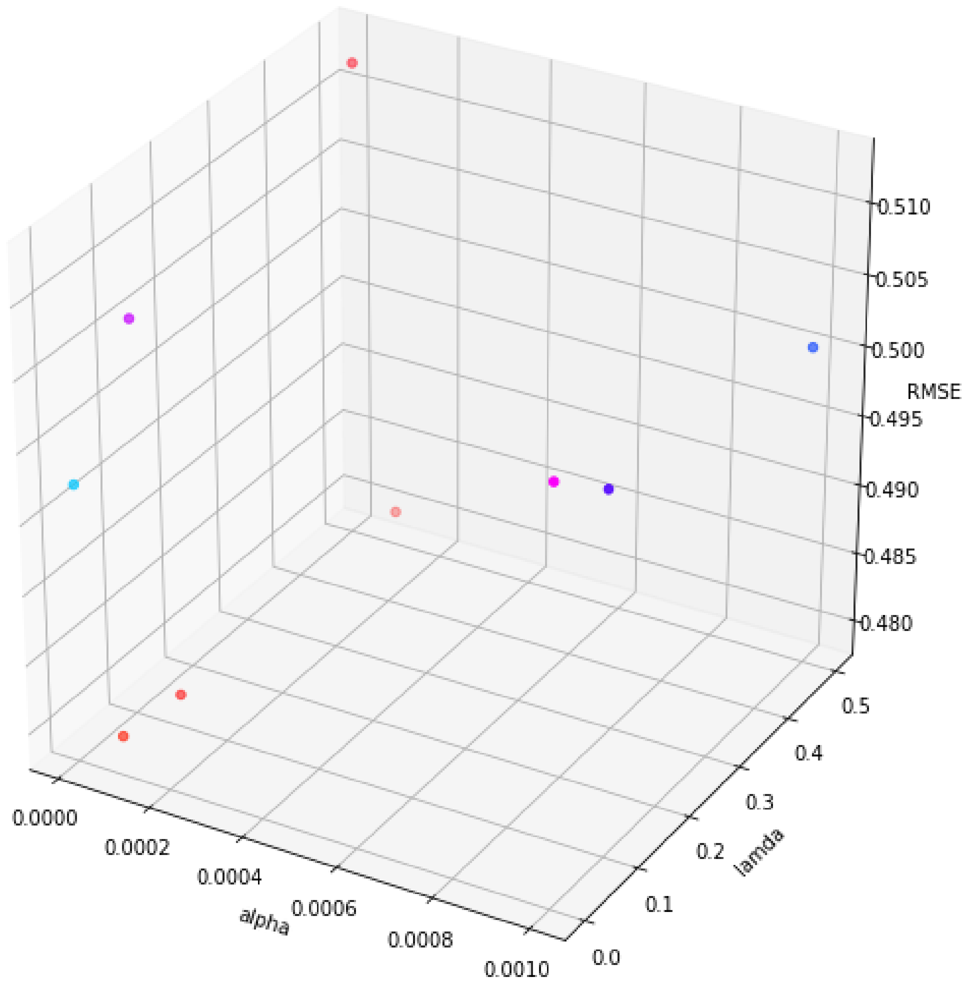
2.0.4 Hypertuning parameters for bank marketing dataset

alpha_com and lamda_com is the array of all the alpha and lamda combinations

avg_rmse is the average of the last rmse for each k fold data For every parameter combination the rmse train and rmse test is tracked

```
In [85]: alpha=[0.0001,0.00001,0.001]
         lamda=[0.0000001,0.1,0.5]
         epochs=20
         k=5
         parameter=gridsearch(alpha,lamda)
         rmse_test=[]
         rmse_last=[]
         rmse_train=[]
         alpha_com=[]
         lamda_com=[]
         avg_rmse=[]
         for i in range (0,len(parameter)):
             k_folded_data=kfold(x_train_bank,y_train_bank,k,x_test_bank,y_test_bank)
             for j in range(0,k):
                     rmsetest,rmsetrain=stochastic_gradient_descent(k_folded_data[j]['x'],k_fo
                     rmse_last.append(rmsetest[-1])
                     rmse_test.append(rmsetest)
                     rmse_train.append(rmsetrain)
             alpha_com.append(parameter[i]['alpha'])
             lamda_com.append(parameter[i]['lamda'])
             avg_rmse.append(np.mean(rmse_last))
```

```
In [92]: from mpl_toolkits import mplot3d
         fig = plt.figure()
         fig.set_figheight(10)
         fig.set_figwidth(10)
         ax = plt.axes(projection= '3d')
         ax.scatter3D(alpha_com, lamda_com, avg_rmse, c=avg_rmse, cmap='hsv')
         ax.set_xlabel('alpha')
         ax.set_ylabel('lamda')
         ax.set_zlabel('RMSE')
         plt.show()
```

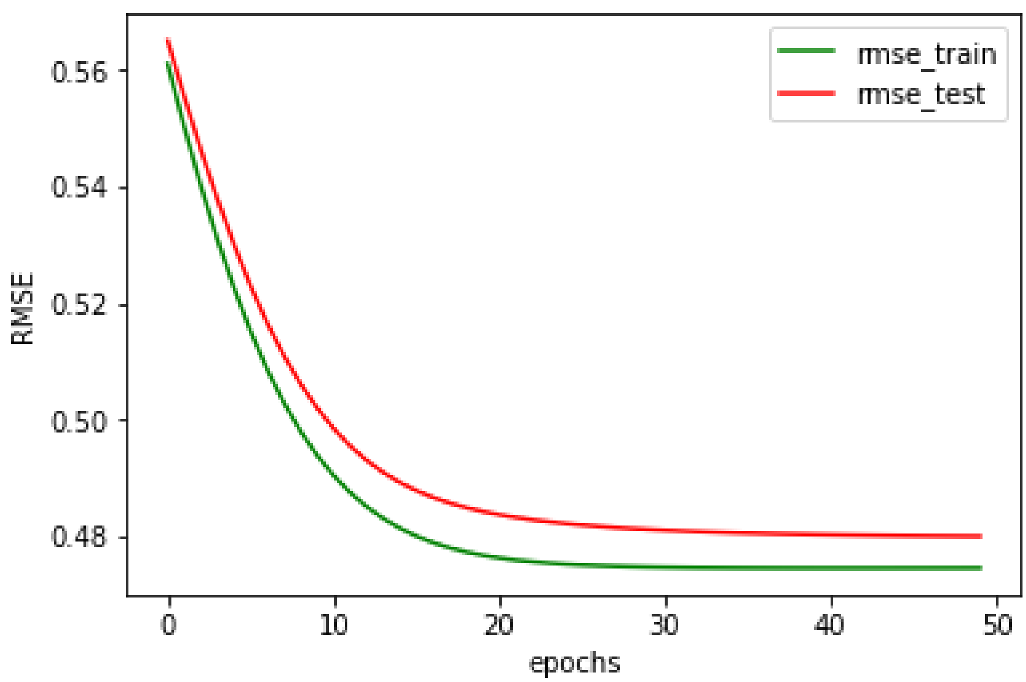


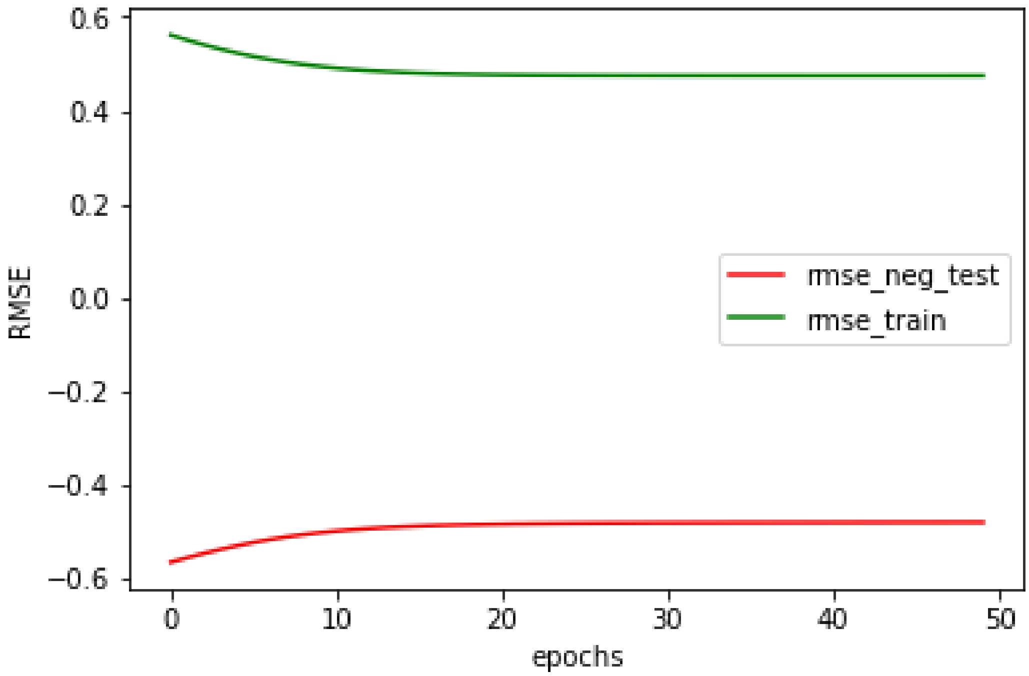
2.0.5 This function gets the optimal value of alpha and lamda by finiding out the index where avg_rmse is minimum

In [113]:
```
def optimal_parameter(avg_rmse,alpha_com,lamda_com):
    lowest_rmse_index=avg_rmse.index(np.min(avg_rmse))
    opt_alpha=alpha_com[lowest_rmse_index]
    opt_lamda=lamda_com[lowest_rmse_index]
    return opt_alpha,opt_lamda
```

In [114]:
```
rmsetest=[]
rmsetrain=[]
epochs=50
alpha,lamda=optimal_parameter(avg_rmse,alpha_com,lamda_com)
rmsetest,rmsetrain=stochastic_gradient_descent(x_train_bank,y_train_bank,alpha,epochs
```

In [115]:
```
plt.plot(np.arange(len(rmsetrain)),rmsetrain,'g',label='rmse_train')
plt.plot(np.arange(len(rmsetest)),rmsetest,'r',label='rmse_test')
plt.xlabel("epochs")
plt.ylabel("RMSE")
plt.legend()
plt.show()


plt.xlabel("epochs")
plt.ylabel("RMSE")
rmsetest=[x*-1 for x in rmsetest]
plt.plot(np.arange(len(rmsetest)),rmsetest,'r',label='rmse_neg_test')
plt.plot(np.arange(len(rmsetrain)),rmsetrain,'g',label='rmse_train')
plt.legend()
plt.show()
```





2.0.6 Hypertuning parameters for wine quality RED dataset

```
In [117]: filename=r"E:\Documents\University of Hildesheim\Machine learning lab\lab5\winequali
          rwine_data = pd.read_csv(filename,delimiter=';')
          rwine_data.head(3)
          Xdata_rwine = rwine_data.loc[:,rwine_data.columns!='quality']
          Ydata_rwine = rwine_data[['quality']]
          Xdata_rwine = (Xdata_rwine - Xdata_rwine.mean())/Xdata_rwine.std() #data normalized
          x_train_rwine, x_test_rwine, y_train_rwine, y_test_rwine =train_test_split(Xdata_rwi
                                                                                      Ydata_rwine,t
                                                                                      test_size=0.2
                                                                                      random_state=

          y_train_rwine=pd.DataFrame(y_train_rwine.values.reshape(-1,1))
          y_test_rwine=pd.DataFrame(y_test_rwine.values.reshape(-1,1))
          x_train_rwine=pd.DataFrame(x_train_rwine.values)
          x_test_rwine=pd.DataFrame(x_test_rwine.values)
```

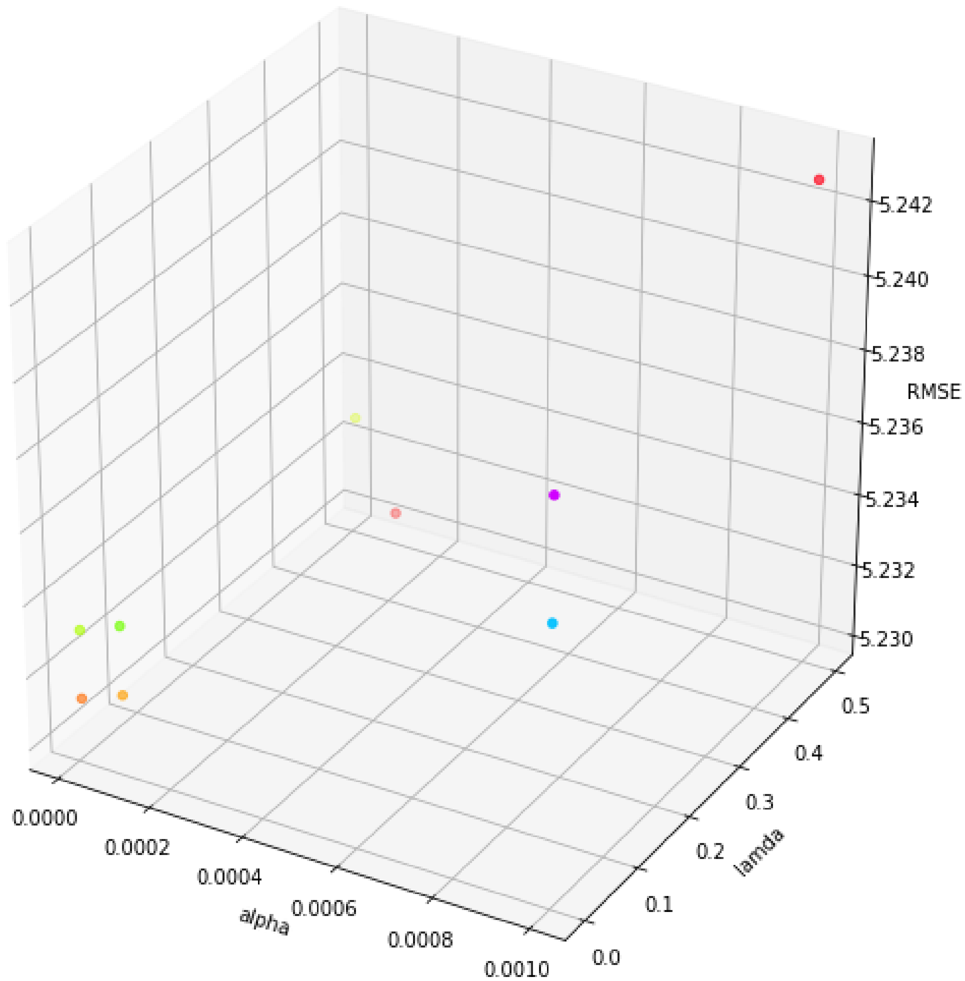
```
In [133]: print('x_train_bank :',x_train_rwine.shape)
          print('x_test_bank :',x_test_rwine.shape)
          print('y_train_bank :',y_train_rwine.shape)
          print('y_test_bank :',y_test_rwine.shape)
```

```
x_train_bank : (1279, 11)
x_test_bank : (320, 11)
```

```
y_train_bank : (1279, 1)
y_test_bank : (320, 1)
```

In [168]:
```
alpha=[0.0001,0.00001,0.001]
lamda=[0.0000001,0.001,0.5]
epochs=20
k=5
parameter=gridsearch(alpha,lamda)
rmse_test=[]
rmse_last=[]
rmse_train=[]
alpha_com=[]
lamda_com=[]
avg_rmse=[]
for i in range (0,len(parameter)):
    k_folded_data=kfold(x_train_rwine,y_train_rwine,k,x_test_rwine,y_test_rwine)
    for j in range(0,k):
            rmsetest,rmsetrain=stochastic_gradient_descent(k_folded_data[j]['x'],k_fo
            rmse_last.append(rmsetest[-1])
            rmse_test.append(rmsetest)
            rmse_train.append(rmsetrain)
    alpha_com.append(parameter[i]['alpha'])
    lamda_com.append(parameter[i]['lamda'])
    avg_rmse.append(np.mean(rmse_last))
```

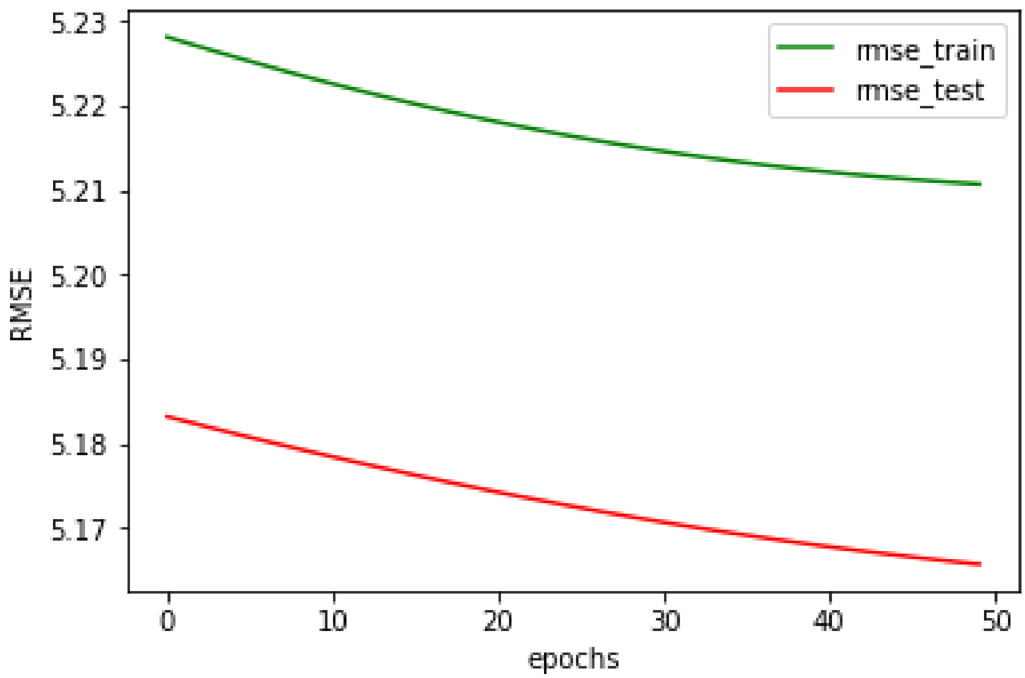
In [171]:
```
from mpl_toolkits import mplot3d
fig = plt.figure()
fig.set_figheight(10)
fig.set_figwidth(10)
ax = plt.axes(projection= '3d')
ax.scatter3D(alpha_com, lamda_com, avg_rmse, c=avg_rmse, cmap='hsv')
ax.set_xlabel('alpha')
ax.set_ylabel('lamda')
ax.set_zlabel('RMSE')
plt.show()
```

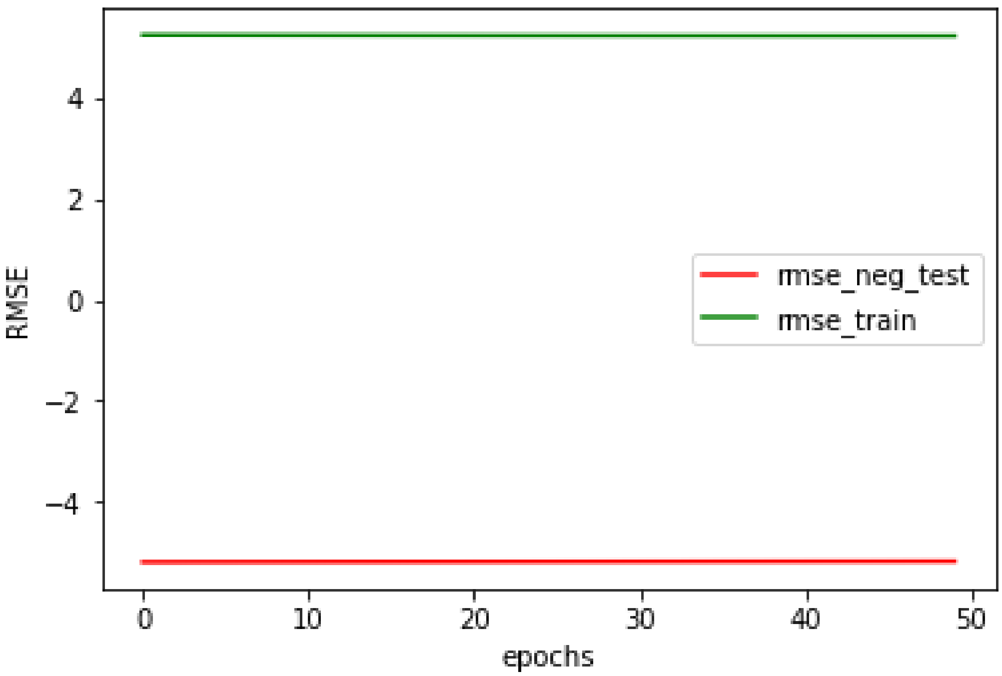



```
In [175]: rmsetest=[]
          rmsetrain=[]
          epochs=50

          alpha,lamda=optimal_parameter(avg_rmse,alpha_com,lamda_com)
          print('OPTIMAL ALPHA :',alpha)
          print('OPTIMAL LAMDA :',lamda)
          rmsetest,rmsetrain=stochastic_gradient_descent(x_train_rwine,y_train_rwine,alpha,epoc

          plt.plot(np.arange(len(rmsetrain)),rmsetrain,'g',label='rmse_train')
          plt.plot(np.arange(len(rmsetest)),rmsetest,'r',label='rmse_test')
          plt.xlabel("epochs")
          plt.ylabel("RMSE")
          plt.legend()
```

```
plt.show()


plt.xlabel("epochs")
plt.ylabel("RMSE")
rmsetest=[x*-1 for x in rmsetest]
plt.plot(np.arange(len(rmsetest)),rmsetest,'r',label='rmse_neg_test')
plt.plot(np.arange(len(rmsetrain)),rmsetrain,'g',label='rmse_train')
plt.legend()
plt.show()
```

```
OPTIMAL ALPHA : 1e-05
OPTIMAL LAMDA : 0.001
```





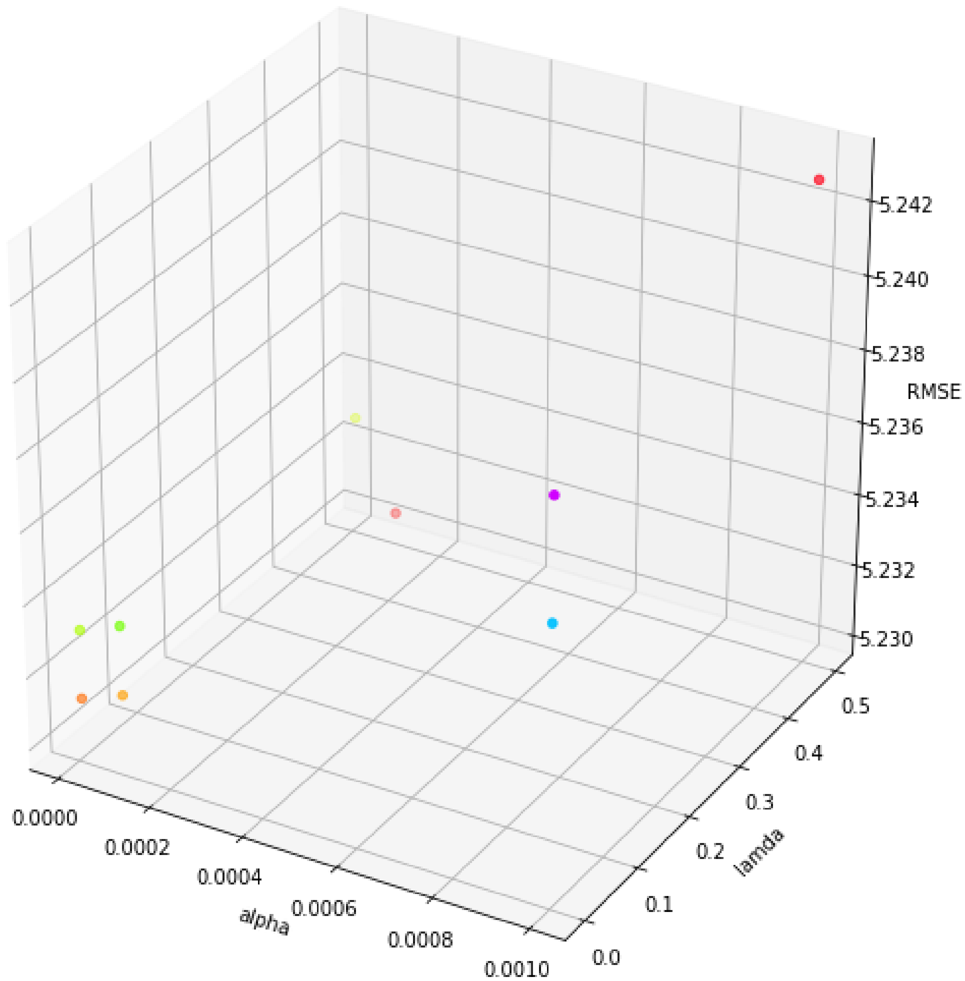
2.0.7 Hypertuning parameters for wine quality WHITE dataset

In [161]:
```
filename=r"E:\Documents\University of Hildesheim\Machine learning lab\lab5\winequali
wwine_data = pd.read_csv(filename,delimiter=';')


Xdata_wwine = wwine_data.loc[:,wwine_data.columns!='quality']
Ydata_wwine = wwine_data['quality']
Xdata_wwine = (Xdata_wwine - Xdata_wwine.mean())/Xdata_wwine.std() #data normalized

x_train_wwine, x_test_wwine, y_train_wwine, y_test_wwine =train_test_split(Xdata_wwi
                                                                           Ydata_wwine,t
                                                                           test_size=0.2
                                                                           random_state=


y_train_wwine=pd.DataFrame(y_train_wwine.values.reshape(-1,1))
y_test_wwine=pd.DataFrame(y_test_wwine.values.reshape(-1,1))
x_train_wwine=pd.DataFrame(x_train_wwine.values)
x_test_wwine=pd.DataFrame(x_test_wwine.values)
```

In [162]:
```
alpha=[0.0000001,0.00001,0.001]
lamda=[0.0001,0.001,0.5]
epochs=20
k=5
parameter=gridsearch(alpha,lamda)
```

```
rmse_test=[]
rmse_last=[]
rmse_train=[]
alpha_com=[]
lamda_com=[]
avg_rmse=[]
for i in range (0,len(parameter)):
    k_folded_data=kfold(x_train_wwine,y_train_wwine,k,x_test_wwine,y_test_wwine)
    for j in range(0,k):
            rmsetest,rmsetrain=stochastic_gradient_descent(k_folded_data[j]['x'],k_fo
            rmse_last.append(rmsetest[-1])
            rmse_test.append(rmsetest)
            rmse_train.append(rmsetrain)
    alpha_com.append(parameter[i]['alpha'])
    lamda_com.append(parameter[i]['lamda'])
    avg_rmse.append(np.mean(rmse_last))
```

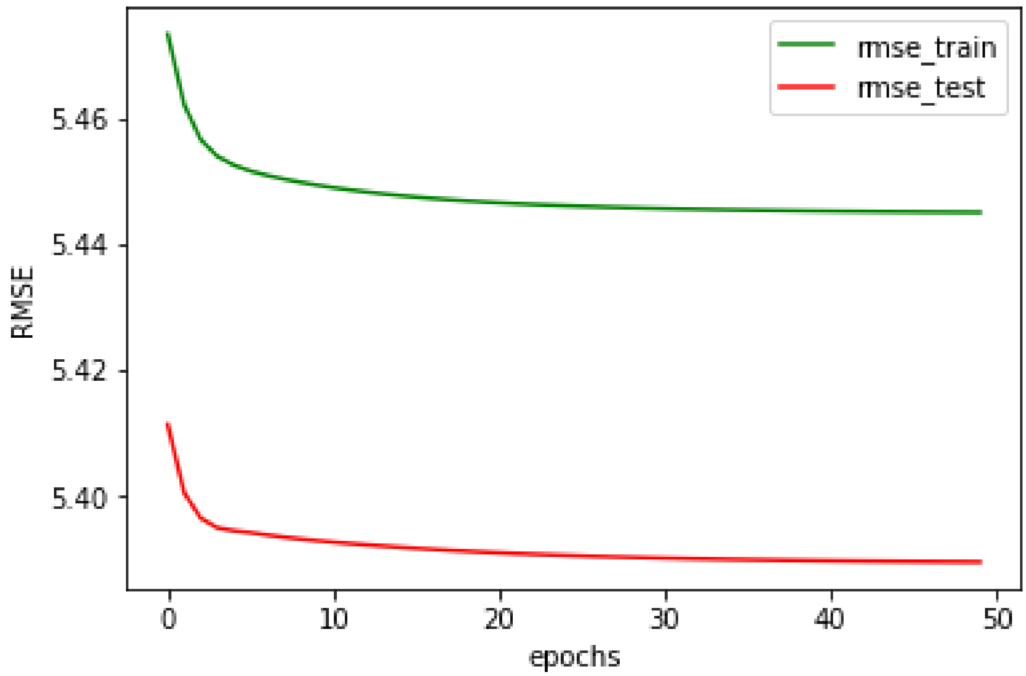
In [169]:
```
from mpl_toolkits import mplot3d
fig = plt.figure()
fig.set_figheight(10)
fig.set_figwidth(10)
ax = plt.axes(projection= '3d')
ax.scatter3D(alpha_com, lamda_com, avg_rmse, c=avg_rmse, cmap='hsv')
ax.set_xlabel('alpha')
ax.set_ylabel('lamda')
ax.set_zlabel('RMSE')
plt.show()
```

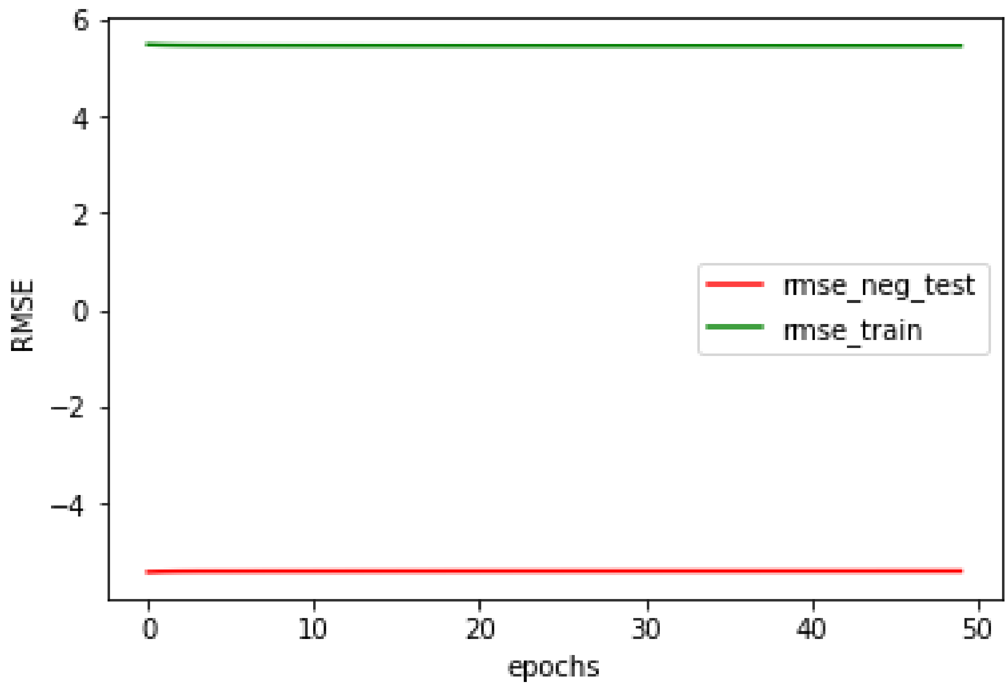


In [170]:
```
rmsetest=[]
rmsetrain=[]
epochs=50
alpha,lamda=optimal_parameter(avg_rmse,alpha_com,lamda_com)
print('OPTIMAL ALPHA :',alpha)
print('OPTIMAL LAMDA :',lamda)
rmsetest,rmsetrain=stochastic_gradient_descent(x_train_wwine,y_train_wwine,alpha,epoc

plt.plot(np.arange(len(rmsetrain)),rmsetrain,'g',label='rmse_train')
plt.plot(np.arange(len(rmsetest)),rmsetest,'r',label='rmse_test')
plt.xlabel("epochs")
plt.ylabel("RMSE")
plt.legend()
plt.show()
```

```
plt.xlabel("epochs")
plt.ylabel("RMSE")
rmsetest=[x*-1 for x in rmsetest]
plt.plot(np.arange(len(rmsetest)),rmsetest,'r',label='rmse_neg_test')
plt.plot(np.arange(len(rmsetrain)),rmsetrain,'g',label='rmse_train')
plt.legend()
plt.show()
```

```
OPTIMAL ALPHA : 0.0001
OPTIMAL LAMDA : 0.5
```





In [ ]: